科技部補助專題研究計畫成果報告
期末報告

以代理人基模擬及真人實驗探究良善社會複雜性之五元素（第 2 年）

計 畫 類 別 ： 個別型計畫
計 畫 編 號 ： NSC 101-2410-H-004-010-MY2
執 行 期 間 ： 102 年 08 月 01 日至 103 年 07 月 31 日
執 行 單 位 ： 國立政治大學經濟學系

計 畫 主 持 人： 陳樹衡

計畫參與人員： 學士級-專任助理人員：游雅惠
博士後研究：張嘉玲

報 告 附 件 ： 出席國際會議研究心得報告及發表論文

處 理 方 式 ：
1. 公開資訊：本計畫可公開查詢
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中 華 民 國 103 年 10 月 31 日

中文摘要： 本研究計畫可概述成四個議題:(1) 施惠者-受惠者賽局(donor-recipient game)框架中社會規範對利社會行為(Pro-Social Behavior) 所扮演之角色 (2) 以艾法洛酒吧賽局(El Farol Bar Game)為例，探討社會網絡與社會偏好對公共資源使用之效率性與公平性之影響 (3) 以網絡信任賽局(network-based trust game)為平台，研究信任與財富創造之間的關係 (4)在預測市場的環境中，性格在資訊加總（或海耶克假設）中的角色。此結案報告將闡述我們對每個議題的發現與貢獻。一般而言，本研究揭開良善社會之形成中，社會規範、社會網路、社會偏好、信任以及性格的重要性。當然，一個兩年期的研究計畫不足以將一個真實的良善社會塑造出來，但我們將往往被主流經濟學和公共政策制定者所忽視的關鍵元素表達出來。這兩年期計畫應被視為將這些關鍵元素納入正式分析重要的第一步。在這個社群網路普及和智慧型社會興起的數位時代，我們認為這些元素的影響力將超過我們的想像。希望這個研究能做為連繫前數位社會和後數位社會間的橋樑。

中文關鍵詞： 良善社會、利社會行為、社會網路、社會偏好、信任、性格、利他性懲罰行為、施惠者-受惠者賽局、艾法洛酒吧賽局、網路信任賽局、預測市場

英文摘要： The research project can be summarized into four series of studies: (1) the role of the social norm in the pro-social behavior in the context of the donor-recipient game； (2) the role of social networks and social preferences in the efficiency and equity of the use of public resources, in the context of the El Farol Bar game, (3) the relationship between trust and wealth creation in the context of the network-based trust game, and (4) the role of personality traits in information aggregation or the Hayek hypothesis, in the context of prediction markets. In this research final report, we shall elaborate on the findings and contribution in each series of the studies. Generally speaking, this research project sheds light on the significance of social norms, social networks, social preferences, trust, and personalities on the formation of a good society. Of course, any good society cannot be built upon a two-year research project, but what has been demonstrated here is the significance of a number of elements that are normally ignored by the mainstream economists and public policy makers. Our two-year research project can be considered as a step to bring these considerations into a formal analysis. In this digital era with the prevalence of social media and the advent of smart societies, we expect to see their even more exceeding influences. Hopefully, our research result can bridge the possible gap between the pre-digital societies and the post-digital societies.

英文關鍵詞： Good Society, Pro-Social Behavior, Social Networks, Social Preferences, Trust, Personality, Altruistic Punishment, Donor-Recipient Game, El Farol Bar Problem, Network-Based Trust Game, Prediction Market

科技部補助專題研究計畫成果報告

（□期中進度報告/■期末報告）

以代理人基模擬及真人實驗探究良善社會複雜性之五元素

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本計畫除繳交成果報告外，另含下列出國報告，共 ___ 份：
□執行國際合作與移地研究心得報告
□出席國際學術會議心得報告

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中　華　民　國 103　年 10　月 25　日

目錄

中文摘要

本研究計畫可概述成四個議題:(1) 施惠者-受惠者賽局(donor-recipient game)框架中社會規範對利社會行為 (Pro-Social Behavior) 所扮演之角色 (2) 以艾法洛酒吧賽局(El Farol Bar Game)為例，探討社會網絡與社會偏好對公共資源使用之效率性與公平性之影響 (3) 以網絡信任賽局(network-based trust game)為平台，研究信任與財富創造之間的關係 (4)在預測市場的環境中，性格在資訊加總（或海耶克假設）中的角色。此結案報告將闡述我們對每個議題的發現與貢獻。一般而言，本研究揭開良善社會之形成中，社會規範、社會網路、社會偏好、信任以及性格的重要性。當然，一個兩年期的研究計畫不足以將一個真實的良善社會塑造出來，但我們將往往被主流經濟學和公共政策制定者所忽視的關鍵元素表達出來。這兩年期計畫應被視為將這些關鍵元素納入正式分析重要的第一步。在這個社群網路普及和智慧型社會興起的數位時代，我們認為這些元素的影響力將超過我們的想像。希望這個研究能做為連繫前數位社會和後數位社會間的橋樑。

關鍵字: 良善社會、利社會行為、社會網路、社會偏好、信任、性格、利他性懲罰行為、施惠者-受惠者賽局、艾法洛酒吧賽局、網路信任賽局、預測市場

英文摘要(Abstract)

The research project can be summarized into four series of studies: (1) the role of the social norm in the pro-social behavior in the context of the donor-recipient game; (2) the role of social networks and social preferences in the efficiency and equity of the use of public resources, in the context of the El Farol Bar game, (3) the relationship between trust and wealth creation in the context of the network-based trust game, and (4) the role of personality traits in information aggregation or the Hayek hypothesis, in the context of prediction markets. In this research final report, we shall elaborate on the findings and contribution in each series of the studies. Generally speaking, this research project sheds light on the significance of social norms, social networks, social preferences, trust, and personalities on the formation of a good society. Of course, any good society cannot be built upon a two-year research project, but what has been demonstrated here is the significance of a number of elements that are normally ignored by the mainstream economists and public policy makers. Our two-year research project can be considered as a step to bring these considerations into a formal analysis. In this digital era with the prevalence of social media and the advent of smart societies, we expect to see their even more exceeding influences. Hopefully, our research result can bridge the possible gap between the pre-digital societies and the post-digital societies.

Keywords: Good Society, Pro-Social Behavior, Social Networks, Social Preferences, Trust, Personality, Altruistic Punishment, Donor-Recipient Game, El Farol Bar Problem, Network-Based Trust Game, Prediction Market

1. Overview of the Two Year Projects

From the year 2012 to 2014, under the project "the Complexity of a Good Society: On the Study of Its Five Elements Using Agent-Based Models and Human-Subject Experiments," (grant number: NSC 101-2410-H-004 -010 -MY2), we have applied agent-based models to four different economic contexts, namely, the donor-recipient game, the El Farol Bar game, the network-based trust game, and the prediction markets. In parallel to the above agent-based modeling, a number of human subject experiments in similar context have been carried out as possible empirical underpinnings of the agent-based models. Over the two years, we were also constantly thinking and working on the connections between the two. This has helped develop new ideas which we have already begun to work with. The title of this on-going work is "Agent-Based Computational Economics and Experimental Economics: A Review of Some Recent Progresses." This working paper will be delivered as a keynote speech by the Principle Investigator, Shu-Heng Chen, at the 5th World Congress on Social Simulation, to be held in Sao Paulo, Brazil, Nov. 4-7, 2014. In this article, we try review the progresses in the research area joining agent-based computational economics (ACE) and experimental economics (EE) since the last survey written by John Duffy in almost a decade ago. Although replicating the results in EE using ACE is still one of the impetuses for the integrated framework, the recent progresses have already moved beyond just replications. It has provided new thinking, hypothesis or theory to the experimental economists in their analytical treatment of data. We term this progress in the interaction between ACE and EE natural allied spiral. The natural allied spiral has two meaning, both broadening and deepening. On the one hand, ACE has helped scale up the settings of EE; one the other hand, ACE has enhanced our understanding of the results of EE. We illustrate this spiral using the well-known learning-to-forecast experiments associated with the heuristic switching models as well as the double auction experiments associated with the individual evolutionary learning models.

Both the heuristic switching models and individual evolutionary learning models are algorithms employed to construct artificial agents. Hence, the other aspect to look at this spiral is the relation between human agents and artificial agents. The idea of using artificial agent in human-subject experiment has a long history, depending on how we define artificial agents. If we consider human-written programs or, using the popular term, avatars, a kind of artificial agents, then we can trace their origin back the use of the strategy method, initiated by Reinhard Selten, in experimental economics. The original purpose of the strategy method is a device to elicit decisions from human subjects, i.e., a transparency attempt. This transparency attempt remains important in the spiral, but they also evolved. In fact, once after some degree of transparency become available, more can be derived or implied. This implied transparency suggests that there are many possible human behaviors there but are not observed simply because our limited sample of subjects. Therefore, for further experimentation, it is desirable to have a larger sample with a greater diversity; nonetheless, a larger sample does not mean recruiting more human subject but using artificial agents instead. When we come to this stage, ACE can take the baton from the hand of EE, and human agents may no longer be needed and can all be replaced by artificial agents.

The rest of this project-end report is organized as follows. Section 2 will give a summary on the conferences, book chapters, and journal articles where the outputs of this project were presented, submitted, or published. **Sections 3 to 6 highlight the main progresses and contributions of this project.** They are arranged with the following titles: donor-recipient game (Section 3), El Farol Bar games (Section 4), network-based Trust Game (Section 5), and prediction markets (Section 6).

2. Research Contribution

The results of the 2-year research project were presented in international conferences, journals and books. The details are listed as follows.

Edited Books and Volumes

1. Advances in Computational Social Science: The Fourth World Congress, Agent-Based Social Systems, Volume 11, (Shu-Heng Chen, Takao Terano, Ryuichi Yamamoto, and Chung-Ching Tai), Springer, 2014.
2. Guest editor (Shu-Heng Chen, Dash Wu, and David Olson), Information Sciences, a special issue on Business Intelligence in Risk Management, 256. 2014. [SCI]
3. Guest editor (Shu-Heng Chen and Sai-Ping Lee), International Review of Financial Analysis, a special issue on Complexity and Non-Linearities in Financial Markets: Perspectives from Econophysics, Vol 23, 2012. [EconLit, FLI]

Referred Journal Articles

1. “Neuroeconomics and Agent-Based Computational Economics,” (Shu-Heng Chen), *International Journal of Applied Behavioral Economics* 3(2): 15-34. 2014.
2. “Competition in a New Industrial Economy: Toward an Agent-Based Economic

Model of Modularity," (Shu-Heng Chen and Bin-Tzong Chie), *Administrative Sciences* 4(3):192-218. 2014.

3. "Social Networks and Macroeconomic Stability," (Shu-Heng Chen, Chia-Ling Chang, and Ming-Chang Wen), *Economics: The Open-Access, Open-Assessment E-Journal*, Vol. 8, 2014-16. http://dx.doi.or/10.5018/economics-ejournal.ja.2014-16 **[SSCI]**
4. "Business Intelligence in Risk Management: Some Recent Progresses," (Shu-Heng Chen, Dash Wu and D Olson), Information Sciences, 256:1-7. 2014. [SCI]
5. "Social Networks, Social Interaction and Macroeconomic Dynamics: How Much Could Ernst Ising Help DSGE? (Shu-Heng Chen, Chia-Ling Chang and Yi-Heng Tseng), Research in International Business and Finance 30: 312-335. 2014. http://dx.doi.org/10.1016/j.ribaf.2012.08.004 [FLI]
6. "Cognitive Capacity and Cognitive Hierarchy: A Study Based on Beauty Contest Experiments," (Shu-Heng Chen, Ye-Rong Du and Lee-Xieng Yang), Journal of Economic Interaction and Coordination, 9(1):69-105. 2013 [SSCI]
7. "Non-Price Competition in a Modular Economy: An Agent-Based Computational Model," (Shu-Heng Chen and Bin-Tzong Chie), Economia Politica: Journal of Analytical and Institutional Economics, XXX(3): 149-175. 2013. [SSCI]
8. "Interactions in the New Keynesian DSGE models: The Boltzmann-Gibbs machine and social networks approach," (Shu-Heng Chen and Chia-Ling Chang), *Economics: The Open-Access*, *Open-Assessment E-Journal*, 6(2012-26). 2012. Retrieved from http://dx.doi.org/10.5018/economics-ejournal.ja.2012-26 **[SSCI]**
9. "To Whom and Where the Hill Becomes Difficult to Climb: Effects of Cognitive Capacity and Personality in Experimental DA Markets," (Shu-Heng Chen, Umberto Gostoli, Chung-Ching Tai and Kuo-Chuan Shih), Advances in Behavioral Finance & Economics, Vol 2, No. 2, 41-75. 2012
10. "Microstructure Dynamics and Agent-based Financial Markets: Can Dinosaurs Return?" (Shu-Heng Chen, Michael Kampouridis, and Edward Tsang), Advances in Complex Systems, Vol 15, supp No 2. 2012 [SSCI, SCI].
11. "不同公司治理情境之股權評價:類神經模糊專家系統之應用"，(陳樹衡、高惠松與李建然) ，管理與系統, Vol. 19, No. 3, 2012.【TSSCI】
12. "Interactions in DSGE Models: The Boltzmann-Gibbs Machine and Social Networks Approach," (Shu-Heng Chen and Chia-Ling Chang), Economics, 2012-26 [SSCI].
13. "Econophysics: Bridges over a Turbulent Current," (Shu-Heng Chen and

Sai-Ping Li), International Review of Financial Analysis, 23:1-10, 2012. [EconLit, FLI]

14. "Market Fraction Hypothesis: A Proposed Test," (Shu-Heng Chen, Michael Kampouridis, and Edward Tsang), International Review of Financial Analysis. 23: 41-54, 2012. [EconLit, FLI]
15. "Liquidity Cost of Market Orders in the Taiwan Stock Market: A Study based on an Order-Driven Agent-Based Artificial Stock Market," (Shu-Heng Chen, Yi-Ping Huang, Min-Chin Hung, and Tina Yu), International Review of Financial Analysis, 23:72-80, 2012. [EconLit, FLI].
16. "Agent-Based Economic Models and Econometrics," (Shu-Heng Chen, C.-L Chang, and Y.-R. Du), Knowledge Engineering Review, 27(2): 187-219, 2012. [SCI]
17. "Varieties of Agents in Agent-Based Computational Economics: A Historical and an Interdisciplinary Perspective," Journal of Economic Dynamics and Control, 36(1):1-25, 2012 [SSCI].

Referred Chapters in Books

1. "Trust, Growth, and Inequality: An Agent-Based Model," (Shu-Heng Chen and Bin-Tzong Chie), in: Yutaka Nakai, Yuhsuke Koyama, and Takao Terano (eds.), *Agent-Based Approaches in Economic and Social Complex Systems VIII: Post-Proceedings of The AESCS International Workshop 2013*, Springer.
2. "Behavioral Macroeconomics and Agent-Based Macroeconomics," (Shu-Heng Chen and Umberto Gostoli), in Sigeru Omatu, Hugues Bersini, Juan Corchado, Sara Rodriguez, Pawel Pawlewski, and Edgardo Bucciarelli (eds.) *Distributed Computing and Artificial Intelligence, 11th Conference.* **Advances in Intelligent Systems and Computing**, Vol 290, 2014, pp. 47-54.
3. Reasoning-Based Artificial Agents in Agent-Based Computational Economics," (Shu-Heng Chen) in Kazumi Nakamatsu and Lakhmi Jain (eds.), Handbook on Reasoning-based Intelligent Systems, World Scientific, 2013, pp. 575-602.
4. "Agent-Based Modeling of the El Farol Bar Problem," (Shu-Heng Chen and Umberto Gostoli), in Alma Lilia García Almanza, Serafin Martinez-Jaramillo, Biliana Alexandrova-Kabadjova, and Edward Tsang (eds.) Simulation in Computational Finance and Economics: Tools and Emerging Applications, IGI Global, 2012, pp. 359-377.
5. "Can Artificial Traders Learn and Err Like Human Traders? A New Direction for Computational Intelligence in Behavioral Finance," (Shu-Heng Chen, Kuo-Chuan Shih and Chung-Ching Tai), in Michael Doumpos, Constantin

Zopounidis, and Panos M. Pardalos (eds.), Financial Decision Making Using Computational Intelligence, Springer Series oon Optimization and Its Applications, Vol. 70, Springer, 2012, pp. 31-65.

6. “Emergent Complexity in Agent-Based Computational Economics,” (Shu-Heng Chen and Shu G. Wang), in Stefano Zambelli and Donald George (eds.), Nonlinearity, Complexity and Randomness in Economics: Toward Algorithmic Foundations for Economics, Wiley-Blackwell, 2012, pp. 131--150.
7. “The Market Fraction Hypothesis under Different GP Algorithms,” (Shu-Heng Chen and Michael Kampouridis and Edward Tsang), in Alexander Yap (ed.), Information Systems for Global Financial Markets: Emerging Developments and Effects, IGI Global, 2012, Chapter 3, pp. 37—54.
8. “Agent-Based Modeling of the Prediction Markets for Political Elections,” (Shu-Heng Chen and Tongkui Yu), in D. Villatoro, J. Sabater-Mir, and J.S. Sichman (Eds.): Multi-Agent-Based Simulation XII, Lecture Notes in Artificial Intelligence (LNAI), Volume 7124, Springer, 2012, pp. 31--43.

Referred Papers in Proceedings

1. “Toward a Spatial Agent-Based Prediction Market: Would the Spatial Distribution of Information Matter?” (Shu-Heng Chen and Bin-Tzong Chie), Proceedings of the 2014 Spring Simulation Multi-Conference (SpringSin’14), Tampa, April 13-16, 2014. pp. 62-67.
2. “Role of Price in Industrial Dynamics,” (Shu-Heng Chen and Bin-Tzong Chie), in 2014 IEEE Proceedings on Computational Intelligence for Financial Engineering (CIFEr’2014), London, UK, March 27-28, 2014, pp. 298-302.
3. “Network-Based Trust Games: An Agent-Based Model,” (Shu-Heng Chen and Tong Zhang), The 5th International Workshop on Emergent Intelligence on Networked Agents (WEIN’13), Saint Paul, Minnesota, USA, May 6, 2013, pp. 60-73.
4. “An Agent-Based Skelton of the Network-Based Trust Games,” (Shu-Heng Chen and Tong Zhang), Society for Modeling and Simulation (SCS) Simulation Series 2013 Proceedings, Book 1, Agent-Directed Simulation Symposium (ADS 2013), San Diego, April 7-10, 2013, pp. 1-6.
5. “Coordination in the El Farol Bar Problem The Role of Social Preferences and Social Networks,” (Shu-Heng Chen and Umberto Gostoli), WCCI 2012 IEEE World Congress on Computational Intelligence, Brisbane, June 11-15, 2012.

Conference Papers

1. “Mechanisms of Trust Formation under Different Conditions of Political Identity,”

(Shu-Heng Chen, Tien-Tun Yang, Ray-May Hsung, Ye-Rong Du, Yi-Jr Lin), *XVIII ISA World Congress of Sociology*, Yokohama, Japan, July 13-19, 2014.

2. "Economics as an Experimental Science: A Review of Some Recent Progresses," (Shu-Heng Chen), *The 12th Taiwan International Symposium on Statistical Physics and Complex Systems* (**StatPhys-Taiwan-2014**), Institute of Physics, Academia Sinica, Taipei, Taiwan, June 28-30, 2014.
3. "The Formation of Risk-Sharing Social Networks," (Shu-Heng Chen, Tong Zhang and Yu Wu), *20th International Conference on Computing in Economics and Finance* (**CEF 2014)**, BI Norwegian Business School and Norges Bank, Oslo, Norway, June 22-24, 2014.
4. "The Donor-Recipient Games: Agent-based vs. Equation-based Modeling," (Shu-Heng Chen, Wen-Jong Ma and Chia-Yao Tseng), *20th International Conference on Computing in Economics and Finance* (**CEF 2014**), BI Norwegian Business School and Norges Bank, Oslo, Norway, June 22-24, 2014.
5. "Agent-based Modeling of the Donor-Recipient Games," (Shu-Heng Chen, Wen-Jong Ma and Chia-Yao Tseng), the *19th Annual Workshop on the Economic Science with Heterogeneous Interacting Agents* (**WEHIA 2014**), Tianjin University, Tianjin, China, June 14-19, 2014.
6. "Aggregation Problem in the New Keynesian DSGE model," (Shu-Heng Chen, Chia-Ling Chang and Yi-Heng Tseng), the *19th Annual Workshop on the Economic Science with Heterogeneous Interacting Agents* (**WEHIA 2014**), Tianjin University, Tianjin, China, June 14-19, 2014.
7. "The Formation of Risk-Sharing Social Networks," (Shu-Heng Chen, Tong Zhang and Yu Wu), *2014 Chinese Economists Society Annual Conference* (**CES 2014**), Jinan University, Guangzhou, China, June 14-15, 2014.
8. "Spatial Modeling of Agent-Based Prediction Markets," (Shu-Heng Chen, Bin-Tzong Chie), *2014 Chinese Economists Society Annual Conference* (**CES 2014**), Jinan University, Guangzhou, China, June 14-15, 2014.
9. "Network-Based Trust Games: An Agent-Based Model," (Shu-Heng Chen, Bin-Tzong Chie and Tong Zhang), *2014 Chinese Economists Society Annual Conference (***CES 2014***)*, Jinan University, Guangzhou, China, June 14-15, 2014.
10. "Agent-Based Modeling of School Admission Systems," (Shu-Heng Chen, Weikai Chen and Connie Wang), *2014 Chinese Economists Society Annual Conference* (**CES 2014**), Jinan University, Guangzhou, China, June 14-15, 2014.
11. "Don't Get Mad, Get Even: Emotions in Ultimatum Games," (Shu-Heng Chen, Chia-Yang Lin), 2014 NeuroPsychoEconomics Conference, Ludwig Maximilian University, Munich, Germany, May 29-30, 2014.
12. "Heterogeneity in Experienced-Weighted Attraction Learning and Its Relation to

Cognitive Ability," (Shu-Heng Chen, Ye-Rong Du), *2014 NeuroPsychoEconomics Conference*, Ludwig Maximilian University, Munich, Germany, May 29-30, 2014.

13. "Order Aggressiveness in Call Auction: Lessons from Closing Call's Information Disclosure New Mechanism in Taiwan," (Shu-Heng Chen, Yi-Heng Tseng and Chia-Ling Chang), *The 5th FMCGC Financial Markets and Corporate Governance Conference*, Queensland University of Technology, Brisbane, Australia, April 22-24, 2014.
14. "Predicting Prediction Markets with Combined Forecasts," (Shu-Heng Chen, Chen-Yuan Tung, Chung-Ching Tai, Brian Chie, and Hung-Wen Lin), *Southwestern Society of Economists 2014 Annual Meeting*, Dallas, Texas, March 11-15, 2014.
15. "Enhancing Interdisciplinary Teaching with Agent-Based Models," (Shu-Heng Chen), *40th Eastern Economic Association Annual Conference*, Boston Park Plaza Hotel, Boston, March 6-9, 2014.
16. "Predicting Prediction Markets with Combined Forecasts," (Shu-Heng Chen, Chen-Yuan Tung, Chung-Ching Tai, Brian Chie, and Hung-Wen Lin), *40th Eastern Economic Association Annual Conference,* Boston Park Plaza Hotel, Boston, March 6-9, 2014.
17. "Don't Get mad, Get even: Emotion in Ultimatum Games," (Shu-Heng Chen, Chia-Yang Lin), *2014 Asia-Pacific Meeting of the Economic Science Association*, University of Auckland Business School, Auckland, New Zealand, February 19-21, 2014.
18. "On the Prediction Accuracy of Prediction Markets: Would the Spatial Distribution of Information Matter?" (Shu-Heng Chen and Bin-Tzong Chie), *International Workshop on Computational, Cognitive and Behavioral Social Science (***CCB'2013***)*, National Chengchi University, Taipei, Taiwan, Dec 6-8, 2013.
19. "Agent-Based Modeling of Donor-Receipts Games," (Shu-Heng Chen, Wen-Jong Ma and Chia-Yao Tseng), *International Workshop on Computational, Cognitive and Behavioral Social Science* (**CCB'2013**), National Chengchi University, Taipei, Taiwan, Dec 6-8, 2013.
20. "On the Prediction Accuracy of Prediction Markets: Would the Spatial Distribution of Information Matter?" (Shu-Heng Chen and Bin-Tzong Chie), The 2013 Winter Workshop on the Economic Science with Heterogeneous Interacting Agents (**Winter ESHIA 2013**), Nanyang Technology University, Singapore, Nov 18-19, 2013.
21. "Agent-Based Modeling of Donor-Receipts Games," (Shu-Heng Chen, Wen-Jong

and Ma and Chia-Yao Tseng), The 2013 Winter Workshop on the Economic Science with Heterogeneous Interacting Agents (Winter ESHIA 2013), Nanyang Technology University, Singapore, Nov 18-19, 2013.

22. "Role of Price in Industry Dynamics: A Modular Perspective," (Shu-Heng Chen and Bin-Tzong Chie), *25th Annual European Association of Evolutionary Political Economy* (**EAEPE'2013**), Paris, France, November 7-9, 2013. "Heterogeneity in Experienced-Weighted Attraction and Its Relation to Cognitive Ability," (Shu-Heng Chen, Ye-Rong Du and Lei Xieng Yang), *2013 Regional Economic Science Association (***ESA***) Conference*, Hotel Paradox, Santa Cruz, California, October 24-26, 2013.
23. "Trust, Growth, and Inequality: An Agent-Based Model," (Shu-Heng Chen and Bin-Tzong Chie), the 8th International Workshop on Agent-Based Approach in Economics and Social Complex Systems (AESCS 2013), Shibaura Institute of Technology, Tokyo, Japan, September 11-13, 2013.
24. "Networks of Wealth and Wealth of Networks," (Shu-Heng Chen and Bin-Tzong Chie), the 18th Annual Workshop on the Economic Science with Heterogeneous Interacting Agents (WEHIA 2013), Reykjavik University, Reykjavik, Iceland, June 20-22, 2013.
25. "Trust, Culture and Development: What We May Learn" (Shu-Heng Chen and Tong Zhang), 2013 Chinese Economists Society Annual Conference (CES 2013), Chengdu, China, June 8-10, 2013.
26. "An Agent-Based Skelton of the Network-Based Trust Games," (Shu-Heng Chen and Tong Zhang), Society for Modeling and Simulation (SCS) Simulation Series 2013 Proceedings, Book 1, Agent-Directed Simulation Symposium (ADS 2013), San Diego, April 7-10, 2013, pp. 1-6.
27. "Network-Based Trust Games: An Agent-Based Model," (Shu-Heng Chen and Tong Zhang), The 5th International Workshop on Emergent Intelligence on Networked Agents (WEIN'13), Saint Paul, Minnesota, USA, May 6, 2013, pp. 60-73.
28. "Cognitive Capacity and Cognitive Hierarchy: A Study Based on Beauty Contest Experiments," (with Ye-Rong Du and Lei Xieng Yang), *Symposium on Decision Science and Brain*, Research Center for Mind, Brain and Learning, National Chengchi University, Taipei, Taiwan. Feb 18, 2013.
29. "Cognitive Capacity and Cognitive Hierarchy: A Study Based on Beauty Contest Experiments," (with Ye-Rong Du and Lei Xieng Yang), *2012 Regional Economic Science Association (ESA) Conference*, Westward Look Resort, Tucson, Arizona, November 16-17, 2012.

3. Social Norms: Donor-Recipient Games

In this project, we studied the donor-recipient game using agent-based modeling. The donor-recipient game is a theoretical environment frequently used to study the influence of social norms on the emergent pro-social behavior, in particular, the prevalence of the altruistic punishment or indirect reciprocity. The conventional approach to this problem is replicate dynamics, which is an equation-based approach. Agent-based modeling, as an alternative to the equation-based approach, provides us a great flexibility to incorporate various considerations of social behavior, information dissemination, learning, and location specificity. In a broader context, this study is a continuation of the recent interest in the comparison between the mean-field model and agent-based model or the individual-based model. We recast this comparison work into the familiar donor-recipient game (benevolence game) for the following two reasons.

First, the donor-recipient game has been used as a benchmark to understand the significance of social norms to pro-social behavior, such as cooperation and costly punishment (altruistic punishment). However, the conclusions are mostly derived from the use of standard replicator dynamics. It is, therefore, interesting to examine its robustness by explicitly addressing the limitations of the analytical tools employed. This comes to our second point of interest. The fundamental process behind the downward causation of norms to individual behaviors involves a highly complex process of individual interactions. The norm is not equivalent to the law; generally speaking, there is no formal central authority or legal institution to enforce its validity. Hence, the consequences of each doing of each individual can be highly heterogeneous and stochastic, depending on their personal encounters in time and in space.

Naturally, one wonders how well the replicate dynamics can harness this underlying complex process. To do so, we extend the replicate-dynamics model of benevolence in our earlier paper (Yu, Chen and Li, 2014, paper already submitted to *Journal of Economic Interaction and Coordination*) into its agent-based counterpart. This extension allows us to examine the sensitivity of a few simplifications made by the former model. The specific important one concerning us in this paper is *time*. The replicator dynamics as a model of group dynamics puts a quite strong regularity on the processes in time, as if all agents share a same time table; the schedule of a sequence of events is homogenously applied to all individuals. In spirit, it is another *tatonnement process*, i.e., no bilateral or trilateral or multilateral transactions can be allowed without having market-clearing condition being satisfied first. Alternatively, no transactions can be allowed under the disequilibrium status. The similar restriction happens in the replicator dynamic model of benevolence: no one can review and revise their strategies unless the reputation associated with the use of each strategy has come to its stationary state.

In reality, people go ahead doing what they prefer to do, feeling no obliged to waiting for others, begin the presence of equilibrium or the presence of stationary distribution. This heterogeneous-in-time among agents can introduce a great amount of disturbances to the replicator dynamics, but that does not mean the inapplicability of the replicator dynamics with the presence of this additional complication. As we may know, the agent-based modeling of Walrasian process actually converges to the original Walrasian equilibrium, and hence becomes another route for the tatonnement process. Nevertheless, only after proper simulations are done, we will not know whether this generality can hold for the case of the benevolence game as well.

Given this motivation, the agent-based used in this paper has several features. First of all, we allow agents to learn and adapt with their own schedule; in other worlds, learning in this agent-based mode is *asynchronous*. Basically, what we do is to define an event and use the *hitting time* of this event to control agents' learning schedule; in this way, the adaptation schedule is not only asynchronous but also stochastic. Second, through the introduced events, we can then also control the frequency of the adaptation of agents, from short, medium to long. Third, in addition to time and frequencies, we also manipulate the information received by agents at two different forms of the word of mouths. At a coarser level, agents are able to see the fitness of each strategy by observing how it contributes to accumulation of wealth of the ``users'', but not the intensity of users' experience with the strategy. At a finer level, agents are also able to observe the intensity and can weigh the raw fitness by this intensity.

These two forms of the word of mouths can be motivated by our daily experiences with the questionnaires in the social medium. Some simply ask the interviewees their evaluations of service without getting additional background information, but some would. Reading the result from the first case, one can only get a rough feeling of how good the service is, but not about its reliability or general applicability.

Agent-based models allow us to take into account of many fine details that the replicator dynamics may have difficult to capturing. Despite this limitation, we find that our agent-based model, qualitatively speaking, has generally led to same result as predicted by the replicator dynamic model. Specifically, its prediction of the emergence of the pro-social behavior is confirmed by several versions of the agent-based model. Discredit those who do not take measure to actively distinguish good-reputation agents from bad-reputation agents can largely enhance the appearance of cooperative behavior.

This study contributes to the literature on the comparative studies of the equation-based models and agent-based models. It enhances our understanding of the two. The paper entitled with "*Agent-Based Modeling of the Donor-Recipient Games*'' has already been presented in four conferences **[Conference papers 4, 5, 19, 21]**. It will be finalized and submitted to *Evolutionary and Institutional Economics Review*.

4. EL Farol Bar Games

We have long been inquiring of the role of government or the role of central (top-down) intervention and regulation. Is it possible to leave citizens themselves to coordinate and solve an ELB-like problem purely from individual actions, not even making an attempt to form an alliance or union? Can the purely individual actions alone bring in a change for the society? Can the good society emerge under an extremely minimal degree of coordination? This series of issues bring in this study.

This study has resulted in two papers. In the first paper, we continue the pursuit of the self-coordination mechanism as studied in the El Farol Bar problem. However, in addition to *efficiency* (the optimal use of the public facility), we are also interested in the *distribution* of the public resources among all agents. Hence, we introduce a two-dimensional El Farol Bar problem, to be distinguished from the early one-dimensional one, which has efficiency as the only concern. We ask whether it is possible to have self-coordinating solutions to the El Farol Bar problem so that the public resources can be optimally used with neither idle capacity nor incurring congestion and, in the meantime, the resources can be well distributed among all agents. We consider this ideal situation an *El Farol version of a ``good society''*. This paper shows the existence of a positive answer to this inquiry, but it requires two elements, which were largely left out in the conventional literature on the El Farol Bar problem. They are social networks and social preferences. We first show, through cellular automata, that social networks can contribute to the emergence of a ``good society''. We then show that the addition of some *inequity-averse agents* can even guarantee the emergence of the ``good society''. This paper entitled with "*Coordination in the El Farol Bar Problem: The Role of Social Preferences and Social Networks*" has already been submitted to *Journal of Economic Interaction and Control*. It is now under the stage of the **second-round review** (the first review has already accepted our revision, but the second reviewer still asks to look into some technical issues).

In the second paper, we carry out a *sensitivity analysis* for an agent-based model of the use of public resources as manifested by the El Farol Bar problem. It is related to the first paper in the following way. The first paper has shown that a good-society equilibrium, characterized by both economic efficiency and economic equality, can be achieved probabilistically by a von Neumann network, and can be achieved m surely with the presence of some agents having social preferences, such as the inequity-averse preference or the `keeping-up-with-the-Joneses' preference. In this study, we examine this fundamental result by exploring the inherent complexity of the model; specifically, we address the effect of the three key parameters related to *size*, namely, the *network size*, the *neighborhood size*, and the *memory size*. We find that social preferences still play an important role over all the sizes considered. Nonetheless, it is also found that when network size becomes large, the parameter, the bar capacity (the attendance threshold), may also play a determining role.

Through the sensitivity analysis, we find that the first conclusion established in the first paper remains quite robust to almost all size-related parameters. The only qualification which we add is that the good society equilibrium is most likely to be a *small-community property*, and exists only there. It is not a metropolitan phenomenon.

The sensitivity analysis also enables us to acknowledge the presence of agents with social preferences. Our extended simulations indicate that social preferences can facilitate the emergence of the good-society equilibrium. The existence of some agents who are inequity-averse or who tend to `keep up with the Joneses' actually has a social value (a positive externality). It is they who make the emergence of the good society from being an exception to being a rule. Their existence is a disturbing force to any `temporal equilibrium' which is not equitable.

The inequity preference, as a psychological gadget, promotes agents to innovate (to search and to learn) and to acquire new strategies to destroy the above-mentioned `temporal equilibrium', making the bar attendance go up and down, above and below the threshold (the bar capacity). These fluctuations further `wake up' those who have already given up learning and prefer to stay home, and encourages them to innovate and to learn, too. In other words, these inequity-averse agents `inspire' those who have been completely `discouraged' and have `rested'. This on-and-on process changes the stability of the inequitable equilibria and re-shapes a large domain of attraction to the good-society equilibrium. Our sensitivity analysis hence shows again that this effect of social preferences is also robust to the change in the size-related parameters.

Nonetheless, as we have seen in a number of scenarios, this on-and-on reshuffling process may go indefinitely long, causing slow convergence or non-convergence. When this happens, the perfect coordination to the ELB problem fails in `limited' time. We have found that this slow convergence or non-convergence property is related to the number of the inequity-averse agents or the number of the KUJ agents in a *V-shaped* manner, indicating that it happens only when *the number of the agents with social preferences is neither sufficiently small nor sufficiently large*.
As long as we have a sufficiently large number of agents with social preferences the basic results on the convergence to the good-society equilibrium remain unchanged.

The second paper entitled with "*On the Complexity of the El Farol Bar Game: A Sensitivity Analysis*" has just been finished and will be submitted to forthcoming conference in 2015 and eventually to a journal.

5. Trust and Social Networks: Network-Based Trust Games

In the network-based trust game, we extend the conventional one-shot two-person trust game into N-person multi-period trust game, and we allow agents to play a dual role, being bot trustor and trustee simultaneously. The literature of trust games actually has already demonstrated this extension, including the acknowledgment of the significance of network embeddedness, but it is our research starts to put all these elements in a coherent body and use it to study the relation between trust and wealth creation.

There are four articles being written under this research framework. Three of the four use agent-based modeling and simulation (to be summarized in Section 5.1), and the last one use the experimental approach (to be summarized in Section 5.2). In fact, this labor division enables us to appreciate the natural allies spiral as we depicted in Section 1. On the one hand, our agent-based models are built upon two key results from the human-subject experiments, namely, the *reciprocity hypothesis* from the repeated trust games and the *network embeddedness* from the 3-person trust games. This direction shows how EE inspire ACE. On the other hand, we realize that the scale that our agent-based models have achieved, i.e., a size of 100 agents playing a dual role of being trustor and trustee with no limit on the possible connections, can be extremely difficult, if not impossible, to be done in laboratory involving 100 human subjects performing the same jobs. Therefore, this direction shows how ACE can scale-up EE.

5.1 The Agent-Based Model

The outputs of this study have three papers, and we shall use AESSC [Book Chapter 1], JASSS (paper submitted *Journal of Artificial Societies and Social Simulation*, under the first revision), and GLER (paper to be submitted to *Global and Local Economic Review*) as their acronyms. The AESCS paper is our skeleton paper in which the basic framework of the agent-based network-based trust games has set and simulated. In this paper, our focus is on the effect of technology on the formation of social network, wealth creation and distribution. We did not do sensitivity analysis in this paper, and hence the result is more tentative. Nonetheless, we do demonstrate a detail analysis of the dynamics of social status (or social mobility). In this regard, our major finding is that while the technology advancement can help build a more egalitarian society, but it also limits the mobility of social status.

In the JASSS paper, we give a quite comprehensive review of the three bodies of the literatures: trust games, network games, and agent-based models of networks which involve the trust element. This review then motivates our more grand integration of the three streams of the literature. We also notice and mention a large body of literature on the agent-based models of business relations and networks. This is because that trust should also play a pivotal role in this context, but the dynamics of trust and business is complex. Therefore, agent-based modeling can shed light on this complex process.

The key research question of JASSS mainly focuses on the role of technology, characterized by the investment multiplier frequently used in the trust game. It comes up with two interesting findings. First, technology has a dual role: it not only contributes to the wealth creation, but also to the network formation. The former result may be well expected, but the latter one is less straightforward. Second, technology can affect the behavior of reciprocity. Our simulation shows that reciprocal behavior will emerge only if the chosen multiplier (the technology level) is higher up to given level. Both of these are of great empirical significance. The first one actually predicts that the two societies may have fundamentally different social networks and social capital if the underpinning technology of them is different. The second one, partially the same coin of the first one, predicts that the reciprocity behavior is not just related to the wealth of the society in a superficial way, but may be fundamentally determined by the underlying technology as well.

The second and the third papers differ mainly in their assumption. Although in some of our other studies, we have already incorporated individual characteristics into the model, in the network-based trust game, we have not considered the significance of this direction. For the JASSS paper, all agents are homogenously myopic in all decisions; however, for the GLER paper, we have modified the assumption, and allow agents to decide the network size through reinforcement learning.

5.2 The Human-Subject Experiments

In addition to the agent-based model, we also conduct a five-person experiment on the network-based trust game. This human-subject experiment coupled with the aforementioned agent-based models enables to see better the natural allied spiral. Basically, the five-person version of the experiment keeps all essential features of the agent-based version of the game except that its multiplier is still fixed. Hence, the network coherence hypothesis considered by the agent-based version is not applicable here. Nevertheless, since a size of five subjects is too limited to investigate the network formation process, the use of state-dependent multiplier may not make much sense in this small-scale experiment. As we mentioned earlier, conducting an equivalent version of the agent-based network-based trust game in human-subject experiments can be extremely challenging. Hence, ACE and EE can both contribute to this research on what they can offer and learn from the other about what they cannot offer. So, what can EE offer ACE in this case?

This research provides the first experimental result on the five-person trust game structured as a network game. It can be considered as the extension of the three-person trust games, which addresses how trust and trustworthiness may be affected when one introduces competition, information sharing, and inside communication through network embeddedness. Ten sessions of the 5-person game were conducted at the NCCU Experimental Economics Lab from Feb 24 to May 26, 2014. These ten sessions are conducted under the same trust-game protocol, namely, a fixed set of players, a dual role, and a repeated game with a termination probability of 0.1. This protocol results in sessions with different durations, form the longest 34 to the shortest 21. In addition to the trust-game experiments, a number of tests with regard to cognitive capacity, personality, and risk attitude were also given to these subjects. Our findings of these experiments are three-fold.

First, the dynamics of the games in terms of income creation and income distribution differs session by session. Some sessions end up with a rich society characterized by a `GDP' gap of zero percent, and some end up with a `poor' society characterized by a `GDP' gap of -30%. While most of the societies (70%) experience growth, stagnation and even decline are also observed. The economic prosperity is not necessarily associated with income distribution. One of the rich societies only has a Gini index of 0.05, whereas the poorest society has a Gini index of 0.15.
Second, these diversified patterns prompt us to seek what are the causes of the observed differences. We address this issue from two possible directions, namely, the initial decisions and the follow-up interactions. Without any prior information or experience, it is interesting to know what determines the first step of these subjects. We find that gender, cognitive capacity, and risk attitude can affect subjects' initial behavior. Once after the game started and information became constantly updated, we study how subjects reacted upon the given information. In this regard, we build an empirical model for the `investment (trust) equation', both collectively and individually. Out of a list of seven variables, we find that the most significant variables are lag-one return ratio and lag-one investment ratio, which by and large supports the reciprocity hypothesis. Finally, we combine what we have learned from the empirical analysis to see how well we may replicate the game dynamics using the data from some representative sessions.

6. Prediction Markets

This line of the research is one of the most exciting progressed made in these two years. The successful outcomes accumulated have already gained the interest of Springer. In July, 2014, we have signed an agreement to publish a book titled with "**Foundations of Prediction Markets: Modeling, Simulation, and Empirical Evidence.**"
http://www.springer.com/business+%26+management/marketing/book/978-4-431-552

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The distinguishing feature of our research is to give a Hayekian analysis of the prediction market using the agent-based model. By the Hayekian analysis, what we mean is to have a real distributed system as an underpinning of the prediction market, and, for that purpose, we have initiated a spatial agent-based prediction market (Section 6.1). As we mention in the beginning of the report, the natural allied spiral between ACE and EE can be exemplified again through this study. Our latest development already incorporates the personality elements into the agent-based model. Hence, in parallel, we also conduct laboratory experiments with human subjects in the context of prediction markets (Section 6.2).

6.1 Agent-Based Prediction Markets

In this research, we apply Thomas Schelling's segregation model as an algorithm to generate social segregation or clusters, which then provides the exogenous social environment or market by which information dissemination is operated. This leads to the development of a simple 3-parameter of spatial agent-based prediction market. The first parameter is related to political ecology, characterized by the number of political parties and their supports. The second and the third parameters concerns two personal traits of agents, both have influence on their personal contribution to information dissemination via market participation: one is tolerance capacity, and the other is exploration capacity.

In one study, we assume that agents are *homogeneous* in their personal traits, and we then simulate the performance of the prediction market conditional on different values of these two parameters. Originally, it was thought that a higher tolerance capacity and a higher exploration capacity can in effect lead to a more efficient information transmission and better prediction accuracy. Quits surprisingly, we found that the result is just the opposite. A further careful analysis shows that, when all agents become more informed and homogeneous due the increase in these two parameters, the trading activeness and trading volume get lower, which in turn forms a negative unfavorable for information dissemination. This finding has been documented in the paper "**Spatial Modeling of Agent-based Prediction Markets: Role of Individuals**" has been accepted by book, *Multi-Agent-Based Simulation* Vol. 15, edited by Emma Norling and Francisco Grimaldo Moreno, to be published by Springer in 2015.

Given our first finding in the spatial agent-based prediction market, in our follow-up study, we assume that agents are *heterogeneous* in their personal traits. It is in this research we are able to include, more formally, the personality psychology, such as agreeableness and extraversion, as a basis of the prediction market. In this study, we find that there is only a slight improvement in prediction accuracy after agents are heterogeneized with their personality traits. The favorite-longshot bias has been slightly corrected by the heterogeneous design. Even though, the two designs do not lead to substantial difference in the aggregate outcome, the heterogeneous model is richer in its micro expressiveness. In this regard, we find the two personality traits can positive affect earnings from trade and hence can be attributed to a worsening income distribution. These findings are already documented in a paper entitled "**The Use of Knowledge in Prediction Markets: How Much of Them Need He Know**?", which has been accepted and will be published in *Journal of Information Science and Engineering*.

6.2 Experimental Prediction Markets

We also collaborate with Bin-Tzong Chie at Tangkang University on his earlier experimental studies of prediction markets. The agent-based models and the experimental markets share some similarities. First, they both apply the same trading mechanism, i.e., the double auction mechanism. Second, they both can have multiple trading `days' or `runs'. Third, they both manipulate the information supplied to the agents. In the agent-based model, the private information is spatially embedded, whereas this private information is through a personal hand-on experience, i.e., a ball-drawing process. While for formality these two can be treated equally, the subtle difference lies in the great unknown of the individual perception (interpretation) of human subjects on this `experience'. For example, we are not sure whether they will form their reservation prices based on their subjective experience. This is very different from our case of artificial agents, in which these perceptions can be directly controlled, for example, using the zero-intelligence-agent device.

Exactly because of this subtlety, the experimental prediction market introduces public information by a public draw. Presumably we may expect that the public information should not have any effect beyond its proper proportion of all information received by the subjects. However, the experimental results show the opposite. A kind of sunspot effect seems to work here (more detailed analysis is needed to be done). Providing artificial agents with the kind of public information is not difficult in agent-based models; nonetheless, we have to also tell our artificial agents how the public information should or should not be treated the same as their private information. It is exactly this kind of autonomy distinguishes ACE from EE.

In addition to the similarity, there are also some striking differences. First of all, as usual, EE has limited number of participants, from 5 to 19, although this difference indeed provides us an opportunity to test the size effect. While the contest market hypothesis already indicates that a large number of firms (agents) are not required for the market to demonstrate the competitive behavior. The experimental results seem to suggest that increasing the number of subjects from 5 to 19 does have a positive effect on prediction accuracy. For the agent-based model, testing the effect of the number of agents is not difficult, while this part has not been done at this stage.

Second, the human subject experiments can directly collect the data of the personal traits, such as personality, and examine its effect. Can our artificial agents have emotion, personality, cognitive capacity or even gender, and in what sense? This is an issue still bothering ACE. For example, while both agreeableness and extroversion have been brought in our JISE paper, and are found to have positive effect on earnings, in human-subject experiment, basically, all five elements of OCEAN can be examined, and it was found that three of five can have an effect on prediction accuracy, namely, conscientiousness, extraversion, and neuroticism. Personality can become meaningful for artificial agents only if we know their implied behavior. For example, the JISE paper also involves the element of extraversion, but its implied behavior is mainly on information acquiring, not trading. Hence, to be consistent, it implication on trading needs to be taken into account, but that essentially requires a different behavioral model of trading.

One essence of this two-year project is to put this fundamental question in the frontier: how to make artificial agents human? To make ACE and EE move constantly in the naturally allied spiral, this is the question needed to be addressed.

7. Academic Activities

To exchange ideas of this project, we held several conferences and seminars, as well as hosting visiting scholars, during the project period (2012-2014):

4th World Congress on Social Simulation
We hosted the 4th World Congress on Social Simulation on September 4-7, 2012, providing 5 keynote speeches, 6 tutorials, 5 special sessions, 1 workshop, and 22 parallel sessions. This conference received 123 presented papers and 150 participants from 22 countries.

http://www.aiecon.org/conference/wcss2012/index.htm	
Herbert Simon Series	
	http://www.aiecon.org/herbertsimon/series%2024/Herbert%20Simon%2024.htm Prof. Richard J. Zeckhauser (1/20/2014-1/21/2014) Group and Individual Decision Making
	http://www.aiecon.org/herbertsimon/series23/Herbert%20Simon23.htm Prof. Carl Chiarella (7/2/2012) Time-Varying Beta: A Boundedly Rational Equilibrium Approach Prof. Tony Xuezhong He Asset Pricing Under Keeping Up with the Joneses and Heterogeneous Beliefs Prof. Carl Chiarella (7/4/2012) A Homoclinic Route to Volatility: Dynamics of Asset Prices under Autoregressive Forecasting Prof. Tony Xuezhong He Heterogeneous Beliefs and Prediction Market Accuracy
Workshop	
	Prof. Cheong Siew Ann Asian Economic Observatory Networks: A Data Driven Approach to Economics Date:1/15/2014
	Prof. Bing-Hong Wang Research on Human Dynamics and Social Complex Systems Date:12/4/2013
Visiting Scholars	
	Prof. Tong Zhang, Prof. Yu Wu, and Prof. Wei Huang Agent-Based Trust Game Visiting period:1/14/2014-2/18/2014
	Prof. Tong Zhang Agent-Based Trust Game Visiting period: 10/23/2012-12/25/2012
	Prof. Hai-Zhen Yang Factors of Market Volatility Visiting period: 10/1/2012-10/31/2012

科技部補助專題研究計畫出席國際學術會議心得報告

日期:103年10月15__日

計畫編號	MOST－101－2410－H－004－010－MY2		
計畫名稱	以代理人基模擬及真人實驗探究良善社會複雜性之五元素		
出國人員姓名	陳樹衡	服務機構及職稱	國立政治大學經濟系教授
會議時間	2014年6月22日至 2013年6月24日	會議地點	Oslo, Norway
會議名稱	(中文) (英文)) The 20th International Conference of Computing in Economics and Finance (CEF 2014)		
發表題目	(中文) (英文) The Donor-Recipient Games: Agent-Based vs. Equation-Based Modeling The formation of Risk-Sharing Group		

一、 參加會議經過

此會議由the Society for Computational Economics (SCE)所主辦，本人與該學會多位歷任主席皆有深厚之學術交誼，故若有經費，其年會本人皆會積極參與，和與會者及學界老友互相切磋琢磨。此次本人共報告兩篇論文，第一篇” The Donor-Recipient Games: Agent-Based vs. Equation-Based Modeling 乃與政大馬文忠、曾嘉瑤合作，第二篇論文“The formation of Risk-Sharing Group”則是與西南財經大學張彤、吳昱兩位教授的合作報告。除參與各場次聽取演講及參與討論之外，本人此次並代表CEF 2015 之主辦單位向SCE主席及理事報告CEF2015 在台舉辦各重要事項之進度及辦理方向，並於大會中為CEF2015宣傳，鼓勵今年與會者明年亦繼續共襄盛舉。

除此之外，本人同時與CEF經常合作之會議公司Simple Meetings 代表Mary McCain 商談有關繼續聘用他們協助CEF2015之契約問題，此事將等該公司提出具體的合約書後決定。

二、 與會心得

此次會議，本人將重點放在目前agent-based macroeconomics 的發展上。誠如其中一位講者，引述Jean-Claude Trichet在擔任歐洲中央銀行主席時的一次演講所說:「當金融危機發生後，現行的

經濟及財務模型所具有的嚴重缺陷就暴露無遺、、、既無法預測危機的來臨，也無法說明危機的產生、、、在面對危機時，令人感到我們被傳統的分析工具所遺棄、、、我們所學到的最重要的一堂課是：只靠單一的工具、方法、或典範是危險的、、、那些在現有模型下假設均質化、效用極大化的個人，無法捕捉到危機下的行為。而代理人基模型(agent-based modeling)，模型，就允許個體間較複雜的互動。各種統體模型，必須更能整合金融系統所扮演的關鍵角色、、、而我也非常歡迎其他學門的投入：物理學、工程學、心理學、生物學。讓這些學門的專家和經濟學家以及銀行家一起合作，將是非常有價值的事。」

本人這期的研究計畫，是在研究影響良善社會形成的五個元素：社會偏好、社會信任、社會網路、社會智慧、以及社會規範。此次的研究，將做為下期預定的代理人基總體模型的基礎之一，代理人基模型，本身就具有跨領域的特性，因為它是一種由下而上（bottom-up）建構模型的概念，利用電腦程式先建構異質性的個體及其所存在的空間，賦予個體不同的特質和行為法則，再經由個體間的互動，由模擬產生動態的總體行為，總體行為是否會達到均衡，或是不斷的變動，則不一定是模擬的觀察重點。在建構模型的過程中，自然就必須融入不同學門的研究：計算機科學、心理、物理、社會學、甚至是地質學等。本人長期從事 agent-based modeling 的研究及推廣，從 90 年代只有極少數人的參與，到現在相當多的學門皆已建構出 agent-based models，並得到越來越多政策決策者的注意，更激勵本人從事此方法的研究。

本次會議中有關代理人基總體模型的論文，偏重政策模擬，大部分利用 Eurace@Unibi 這個代理人基總體模型加以調整來進行。它是 Herbert Dawid（德國 Bielefeld 大學)等人，改進 Eurace 代理人基總體模型而成。Eurace 為歐盟 FP6 的計畫之一，結合歐洲多位代理人基重量級學者（除 Herbert Dawid 外，尚包括 Domenico Delli Gatti, Mauro Gallegati 等人共同合作而成。Eurace@Unibi 是一個封閉式的、有空間概念的經濟體，此模型中，含有勞動部門、投資及消費部門、以及金融和信貸市場。其目的即是做為政策分析和總體經濟議題研究的平台，尤其是關係到科技發展及傳播方面的政策模擬，譬如 Herbert Dawid 的團隊近年來，所從事的關於產業升值的政策，包括提升勞動力的補助、協助企業投資技術方面的政策、針對特定區域性的政策、無針對性的政策等，以及各種政策對所得分配的影響。

由本人所帶領的人工智慧經濟學研究中心，其在代理人基模擬的技術上，在全球亦屬知名，但礙於人力和財力之不足，無法建構如 Eurace 或 Eurace@Unibi 之類仿歐盟經濟體之大型模型。直至今年，始獲科技部補助經費，始可開始建構屬於台灣的代理人基總體模型。然而經費仍舊有限，不能像歐盟般，每年提供數什名博士後研究之經費，始能完成 Eurace 及其新的版本。但本人仍將竭盡所能，善用所有資源，來建構屬於台灣的代理人基總體模型，為台灣的經濟政策，提供多一種模擬及分析的工具。

三、 發表論文全文或摘要

請見附檔

四、 建議

無

五、攜回資料名稱及內容

此次會議資料袋中，僅有議程、Norwegian Business School 簡介及 Oslo 簡介。會議議程請見：http://comp-econ.org/CEF_2014/Schedule.htm

六、其他

無

Agent-Based Modeling of the Donor-Recipient Games

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Abstract

In this paper, we study the donor-recipient game using agent-based modeling. The donor-recipient game is a theoretical environment frequently used to study the influence of social norms on the emergent pro-social behavior, in particular, the prevalence of the altruistic punishment or indirect reciprocity. The conventional approach to this problem is replicate dynamics, which is an equation-based approach. Agent-based modeling, as an alternative to the equation-based approach, provides us a great flexibility to incorporate various considerations of social behavior, information dissemination, learning, and location specificity.
Keyword: The Donor-Recipient Game, Agent-Based Models, Social Norm, Altruistic Punishment, Social Learning, Word of Mouth, Basin of Attraction

1 Motivation and Introduction

In this paper, we compare the system behavior driven by group interactions (replicator dynamics) with that driven by individual interactions (agent-based model). In a broader context, this study is a continuation of the recent interest in the comparison between the mean-filed model and agent-based model or the individual-based model (Vinkovic and Kirman, 2006; Aoki and Yoshikawa, 2012; Van Dyke Parunak, 2012; Burger, Haskovec, and Wolfram, 2013). We recast this comparison work into the familiar *donor-recipient game* (*benevolence game*) for the following two reasons.

First, the donor-recipient game has been used as a benchmark to understand the significance of social norms to pro-social behavior, such as cooperation and costly punishment (altruistic punishment) (Ohtsuki and Iwasa, 2007; Ohtsuki, Iwasa, and Nowak, 2009; Yu, Chen and Li, 2011). However, the conclusions are mostly derived from the use of standard replicator dynamics. It is, therefore, interesting to examine its robustness by explicitly addressing the limitations of the analytical tools employed. This comes to our second point of interest. The fundamental process behind the downward causation of norms to individual behaviors involves a highly complex process of individual interactions. The norm is not equivalent to the law; generally speaking, there is no formal central authority or legal institution to enforce its validity. Hence, the consequences of each doing of each individuals can be highly heterogeneous and stochastic, depending on their personal encounters in time and in space.

Naturally, one wonders how well the replicate dynamics can harness this underlying complex process. To do so, we extend the replicate-dynamics model of benevolence as studied by Yu, Chen and Li (2011) into its agent-based counterpart. This extension allows us to examine the sensitivity of a few simplifications made by the former model. The specific important one concerning us in this paper is *time*. The replicator dynamics as a model of group dynamics puts a quite strong regularity on the processes in time, as if all agents share a same time table; the schedule of a sequence of events is homogenously applied to all individuals. In spirit, it is another *tatonnement process*, i.e., no bilateral or trilateral or multilateral transactions can be allowed without having market-clearing condition being satisfied first (Fisher, 1983). Alternatively, no transactions can be allowed under the disequilibrium status. The similar restriction happens in the replicator dynamic model of benevolence: no one can review and revise their strategies unless the reputation associated with the use of each strategy has come to its stationary state.

In reality, people go ahead doing what they prefer to do, feeling no obliged to waiting for others, begin the presence of equilibrium or the presence of stationary distribution. This heterogeneous-in-time among agents can introduce a great amount of disturbances to the replicator dynamics, but that does not mean the inapplicability of the replicator dynamics with the presence of this additional complication. As we may know, the agent-based modeling of Walrasian process actually converges to the original Walrasian equilibrium, and hence becomes another route for the tatonnement process (Gintis, 2007). Nevertheless, only after proper simulations are done, we will not know whether this generality can hold for the case of the benevolence game as well.

Given this motivation, the agent-based used in this paper has several features. First of all, we allow agents to learn and adapt with their own schedule; in other worlds, learning in this agent-based mode is *asynchronous*. Basically, what we do is to define an event and use the *hitting time* of this event to control agents learning schedule; in this way, the adaptation schedule is not only asynchronous but also stochastic. Second, through the introduced events, we can then also control the frequency of the adaptation of agents, from short, medium to long. Third, in addition to time and frequencies, we also manipulate the information received by agents at two different forms of the word of mouths. At a coarser level, agents are able to see the fitness of each strategy by observing how it contributes to accumulation of wealth of the "users", but not the intensity of users' experience with the strategy.[1] At a finer level, agents are also able to observe the intensity and can weight the raw fitness by this intensity.

[1]These two forms of the word of mouths can be motivated by our daily experiences with the questionnaires in the social medium. Some simply ask the interviewees their evaluations of service without getting additional background information, but some would. Reading the result from the first case, one can only get a rough feeling of how good the service is, but not about its reliability or general applicability.

Table 1: Payoff Matrix of the Donor-Recipient Game

	Donor		
	Cooperate (C)	Defect (D)	Punishment (P)
Recipient	(b, -c)	(0,0)	(-β, -α)

2 The Agent-Based Model

2.1 Donor-Recipient Game

In our agent-based model, agents are randomly matched in pair and in time. Each point in time (step) two agents are randomly chosen out of the whole population as a pair to play the donor-recipient game. One of them plays the role of the donor, and the other one plays the role of recipient. These roles are also randomly determined. The donor could do of the following three possible actions: cooperation (C), defection (D), and punishment (P). The recipient can do nothing reciprocally. If the donor decide to "cooperate", he will make a contribution to the recipient at his own cost of c, but it in turn will increase the wealth of the recipient by b. If the donor decides to "defect", he will give nothing to the recipient, and recipient also gains nothing from his action. The donor can also make a punishment to the recipient again at his own cost α and that will cause a damage of β to the recipient's wealth. Normally, we assume that b is greater than c, and β is greater than α. The consequence of each choice made by the donor can then be summarized by a payoff matrix shown in Table 1. The payoffs that agents receive in each run of the game will be constantly cumulatively attributed to agents' wealth. Denote the wealth of agent i in time t by $W_i(t)$.

In addition to the payoff, there is an additional consequence imposed on the donor, i.e., his social status as recognized by the society. In a simple setting, there are only two statuses available in the society, namely, a good man (G) or a bad man (B). As to which status being assigned, it is determined by the ruling *social norm*. Basically, the social norm will decide the donor's status or reputation based *what he did and to whom*: did he do good thing for good man or bad thing for bad man, etc. In other words, the social norm is a mapping:

$$\mathbb{N} : \mathbf{A} \times \mathbf{R} \rightarrow \mathbf{R}, \tag{1}$$

where $\mathbb{N}$ denotes the ruling social norm, $\mathbf{A}$ is the action space for the donor,

$$\mathbf{A} = \{C, D, P\},$$

and $\mathbf{R}$ is the space of social statuses or reputations,

$$\mathbf{R} = \{G, B\}.$$

In this article, for making comparison, we focus on the three norms studied by Yu, Chen and Li (2011), namely, *simple social norm*, *weakly augmented social norms*, and *strongly augmented social norms*. The mapping of these three norms from $\mathbf{A}$ to $\mathbf{R}$ are shown in Table 2.

Table 2: Social Norms

A ↓	R →	Simple Social Norm G	Simple Social Norm B	Weakly Augmented Social Norm G	Weakly Augmented Social Norm B	Strongly Augmented Social Norm G	Strongly Augmented Social Norm B
C		G	G	G	G	G	G
D		B	G	B	G	B	B
P		NA	NA	B	G	B	G

The simple social norm is applicable to a society that punishment is not an option, i.e., the action space **A** is further restricted to either action C or D. Under this norm, a man is considered as a bad man only if he did bad thing (D) for a good man (G). In other cases, he will be recognized as a good man. The augmented social norm augments the action space with the punishment option. As in the simple social norm, a man is recognized as a bad man if he did a bad thing (D or P) to a good man (G). However, an interesting issue arising here is what we should do for the bad man. Is just walking-away and hands-off (defect) enough, or should we actually make some efforts (a cost of α) to punish him? This punishment in the literature is known as *altruistic punishment* or *costly punishment* (Fehr and Gächter, 2002). We, therefore, further distinguishes the augmented social norm into a weak version and a strong version. The *weakly augmented norm* does not consider man taking no action (defect) to a bad man as an evil thing, but the *strongly augmented norm* does and hence a man who did nothing to a bad man will be recognized as a bad man as well.

2.2 Behavioral Rules

Given this variety of social norms, a natural question is the differential effects of social norms on the emergent pro-social behavior; specifically, what are required social norms for enhancing pro-social behavior? To answer this question, we need to know the behavioral rules followed by different agents under different social norms. In the donor-recipient game, a behavioral rule or a strategy can be defined as a mapping from the reputation of the recipient to the taken action,

$$s : \mathbf{R} \to \mathbf{A}. \tag{2}$$

For example, a contribution made to a good man, but a defection to a bad man is a strategy; regardless of the reputation of the recipient, always being benevolent is another strategy. The cardinality of the strategy space, $\mid \mathbf{S} \mid$, is simply $\mid \mathbf{R} \mid$ to the power of $\mid \mathbf{A} \mid$, i.e.,

$$\mid \mathbf{S} \mid = \mid \mathbf{R} \mid^{|\mathbf{A}|}.$$

However, not all strategies are interesting or intuitive. For example, D for G, and C for B (DC for abbreviation) is not intuitive, since if a man who is selfish and will not give a penny for a good man, then why should bother him to care about a bad man? In a similar vein, we follow the reduction made by Yu, Chen and Li (2011) to exclude PC, and PD, as

Table 3: Strategy Space

	Simple Strategy Space		Augmented Strategy Space	
S	G	B	G	B
s_1	C	C	C	C
s_2	C	D	C	D
s_3	D	D	D	D
s_4			C	P

well as DP and PP. This leaves a small strategy space as shown in Table 3. Notice that since the punishment action is not an option for agents under the simple action space, there are only three strategies available for agents, namely, CC, CD, and DD. For the augmented action space, there is an additional strategy, CP.

2.3 Adaptive Behavior

The strategy (behavioral rule) that the agent uses to play the game will evolve over time with his learning. In this article, we assume that agents are able to learn from other participants' experience; hence, it is a style of *social learning*. As in most models of adaptive agents, we assume that agents will constantly review and revise their strategy. In other words, after certain duration of time, agents will review his current strategy and decide whether he shall switch to other alternatives. In this model, we assume that agents will consider the possibility of changing the incumbent strategy only after they have played the role of donor for every k times.[2] Hence let $t_{i,j}$ be the *hitting time* that agent i plays the role of donor for the jth time, then for agent i learning will be activated for agent i only in $t_{i,nk}$ ($n = 1, 2, ...$). Since $t_{i,j}$ is a random increasing series, agents review and revise their strategy in an *asynchronous* manner.[3] Also, since it is possible that when an agent i is called, the role assigned to him is a recipient, rather than a donor, to distinguish this more general hitting time, we shall denote the time that the agent i is called h times into the game as $t_{i,h}$. Obviously, $\{t_{i,j}\}$ is a subsequence of $\{t_{i,h}\}$. For an illustration of this learning schedule, Figure 1 gives the schedule of the agents 47 and 98 in a typical run under simple social norm.

When $t_{i,nk}$ is up, agent i will randomly pick up a strategy from the strategy set as a possible alternative for the current strategy, i.e.,

$$s' \in \mathbf{S} \setminus \{s_{t_{i,nk}}\}, \ \ \mathbf{S} = \{s_i\}_{i=1}^{3 \ or \ 4}$$

where $s_{t_{i,nk}}$ is the strategy used in time $t_{i,nk}$ by agent i. One of the two, i.e., either $s_{t_{i,nk}}$ or s', will be *stochastically* chosen for him to play the role of donor next time. This stochastic

[2]Later on we will further add one more condition, i.e., there have been K agents experiencing the role of donor since last adaptation. At this point, K is set to one, and hence it is not actually binding.

[3]While asynchronized learning is not new in agent-based computational economic modeling, most ACE models are still built upon synchronized learning.

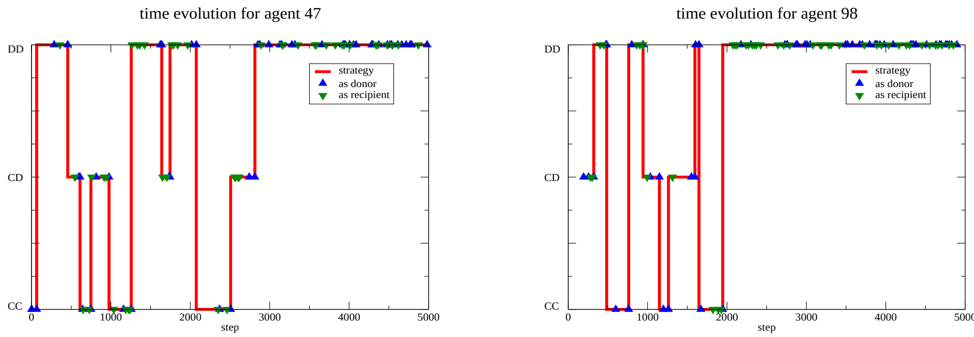

Figure 1: Adaptation Time: Agent 47 (Left) and Agent (98), Simple Social Norm

In the figure above, the upward triangle indicates the time to play the role of donor, and the downward triangle indicates the time to play the role of recipient. Change may happen every upon two times that the agent has played the role of donor. In this diagram, we can see that agent 47 played the role of donor at time 2 and 4, and hence adaptation happens at time 4, and he decided to switch from strategy 'CC' to'DD'. After that he has played the role of donor again at time 286 and 359; hence adaption happened at time 359, and this time he decided to switch from 'DD' to 'CD'.

choice is characterized by the familiar logistic (Boltzmann-Gibbs) distribution, which is based on the *gain* in the performance of the incumbent strategy relatively to the that of the alternative.

2.3.1 Fitness Function

To determine this gain, we shall start with the increments in wealth contributed by the employment of the strategy in question. We shall use $\Delta W_i(t)$ as the increment in wealth.

$$\Delta W_i(t) = W_i(t) - W_i(t-1) \tag{3}$$

Obviously, when the agent i is not active (not called to the game) in time t, there will be no increment in wealth, i.e., $\Delta W_i(t) = 0$. Hence, $\Delta W_i(t)$ can be non-zero only at $t_{i,h}$, and, only a subsequence of $\{\Delta W_i(t)\}$ is non-trivial, i.e., $\{\Delta W_i(t_{i,h})\}$, or, simply, $\{\Delta W_i(t_h)\}$ when the other subscript i is redundant. Given the assumption of social learning, we shall assume that the information $\{\Delta W_i(t)\}$ is publicly observable for all agents i and for all time t.

When it is the time for agent i to update his strategy, the *strength* of the strategy of s ($s \in \mathbf{S}$) is derived based on the idea of the *word-of-mouth* mechanism. First, how, on the average, each strategy when *alive* contributes to the increment in the wealth of each agent i is figured out, i.e.,

$$\overline{\Delta W}_{l,t_{i,nk}}(s) = \frac{\sum_{t \le t_{i,nk}} \Delta W_l(t \mid s)}{f_{l,s}(t_{i,nk})},$$

where $\Delta W_l(t \mid s)$ is the increment in wealth conditional upon when the strategy s is alive, and $f_{l,s}(t_{i,nk})$ is the number of times (the frequency) that the strategy s adopted by agent

i up to time $t_{i,nk}$. Second, the *strength* of each strategy in time $t_{i,nk}$ is then the average of the contribution of each strategy taken over all agents.

$$H_{t_{i,nk}}(s) = \frac{\sum_{l=1}^{N} \overline{\Delta W}_{l,t_{i,nk}}(s)}{N}. \tag{4}$$

The above formulation of the word-of-mouth mechanism treats each agents' experience of s equal. It does not consider their heterogeneity in the intensity of the experience with different strategies. It is very likely that some agents are more frequently under the exposure of the strategy s than other agents. In this case, their experience of the strategy should be weighted more than those who are less experienced with s. Hence, an alternative formulation is to take the *weighted*, instead of the simple, average as follows.

$$H^{f}_{t_{i,nk}}(s) = \frac{\sum_{i=1}^{N} \sum_{t \le t_{i,nk}} \Delta W_l(t \mid s)}{\sum_{l=1}^{N} f_{l,s}(t_{i,nk})}. \tag{5}$$

The setting of Equations (4) and (5) allows us to distinguish two kinds of word of mouth. Putting it in a simple way, Equation (4) allows agents to know how many agents like or dislike an strategy, but does not release the information on how much they had experienced with that strategy. Hence, a customer who visited a restaurant once but disliked it is equally weighted with another customer who visited it ten times and enjoyed it every time. We shall call this kind of word of mouth the *social learning with coarser information* to distinguish it from the case that the information received is weighted by the intensity of users' experience. We shall call the latter *social learning with finer information*. The reason that we propose this two designs is because these two kinds of word of mouth co-exist and it is interesting to see whether they do have no trivial effect as in the case of the benevolence game.

2.3.2 Strategy Switching Mechanism

Given the fitness function described as above, our asynchronized learning can be described with the following familiar logistic distribution.

$$\begin{aligned} Prob(s^* = s) &= \frac{\exp(\lambda H_{t_{i,nk}}(s))}{\exp(\lambda H_{t_{i,nk}}(s)) + \exp(\lambda H_{t_{i,nk}}(s'))} \\ &= \frac{1}{1 + \exp(\lambda(H_{t_{i,nk}}(s') - H_{t_{i,nk}}(s))}, \end{aligned} \tag{6}$$

where s denotes the strategy currently employed, and s' be the competing candidate, which is randomly selected from $\mathbf{S} - \{s\}$. It would be interesting to notice that the agent does not evaluate all possible alternatives in $\mathbf{S}$ but only one of them. Alternatively, if the fitness is based on the weighted average, then the stochastic choice (6) becomes

$$\begin{aligned} Prob(s^* = s) &= \frac{\exp(\lambda H^{f}_{t_{i,nk}}(s))}{\exp(\lambda H^{f}_{t_{i,nk}}(s)) + \exp(\lambda H^{f}_{t_{i,nk}}(s'))} \\ &= \frac{1}{1 + \exp(\lambda(H^{f}_{t_{i,nk}}(s') - H^{f}_{t_{i,nk}}(s))}, \end{aligned} \tag{7}$$

Table 4: Tableau of Control Parameters

Parameter	Interpretation	Value
$(b, c, \alpha, \beta, \mu)$	Parameters of the Benevolence Game	(2,3,1,4, 0.02)
N	Number of Agents	100
$W_i(0)$	Initial Wealth	1,000
(k, K)	(Required Experience for Adaptation,	(2,1)
	Required Numbers of Experienced Agents	(1,000, 50)
	for Adaptation)	(10,000, 50)
λ^{-1}	The Inverse of the Intensity of Choice	0, 1, 2, 3, 4, 5, 16, 64, 256

This design is atypical in the common practice of ACE. Normally, we would expect that all strategies will be evaluated as what the standard adaptive belief system, promoted by Cars Hommes, does (Hommes, 2006). However, here, we motivate a different searching behavior: when the strategy-switching time comes to the agent, he *immediately* makes such a decision based on the review of the first alternative that comes cross him, instead of waiting for the review of all possible strategies. This *first-come first-served* decision making is certainly less computational demanding, in particularly, when the size of **S** is large. Also, it requires less information than the standard adaptive belief system may demand, since we may consider the first-come one as the one that its performance information is most readily accessible. Hence, it has a virtue close to Herbert Simon's bounded rationality.

3 Simulation Designs

Our simulation of the agent-based model is to be compared with the results of replicator dynamics obtained by Yu, Chen and Li (2011); therefore, we take the same values for the major five parameters of the donor-recipient games as those set in Yu, Chen and Li (2011). For the part of agent-based model, while the mean-field model does not suggest a natural choice for the number of agents, we think that a medium size will be necessary for facilitate both comparison and computing work. Hence, we set the number of agents to 100. Initial wealth is set to one thousand, which is large enough to be treated as a stock given that the size of flow will be limited to -4 (β) to +3 (b). However, since the driving force for the evolution of strategies is based on the increments in wealth, this setting is not that critical.

The next two parameters, k and K, are however critical, at least, conceptually. This is because the former control how frequently the individual agents can review and revise their strategies, whereas the latter control how frequently the society as a whole can do such things. Needless to say, the larger the value of k and K the lower the adaptation frequency. Since the adaptation frequency is a key parameter of the replicator dynamics, we can actually choose different values of k and K to examine whether the learning speed plays a role in the relation between the replicate dynamics and the agent-based model. Hence, to achieve this goal, we consider three pairs of k and K which characterizes a high,

Table 5: Codes for Simulation Scenarios

Code	Adaptation Frequency	Information Granularity
II-A	High	Coarse
II-B	High	Fine
III-A	Medium	Coarse
III-B	Medium	Fine
IV-A	Low	Coarse
IV-B	Low	Fine

a medium, and a low frequency of adaptation, respectively. They are $(2, 1)$, $(1,000, 50)$, and $(10,000, 50)$. These settings of parameters are summarized in Table 4.

Finally, as we mentioned earlier, there are two design of information granularity being consider, i.e., the coarser information and the finer information. They concern the exact stochastic choice model for strategy switching, and are already specified in Equations (4) and (5). However, there is one parameter, namely, the intensity of choice (λ), needs to be specified. Here, from high to low, we consider several different values of the λ. Since we are interesting in the limit case when λ goes to infinity, we use λ^{-1} instead of λ in Table 4.

To make our simulation results easy to present, we label the three frequency schemes by II (high frequency), III (medium frequency), and IV (low frequency), and reserve Label 'I' for the baseline model, i.e., the replicator dynamics. We further label the social learning with coarser information as 'A' and that with finer information with 'B'. Hence, together we have six different simulation scenarios II-A, II-B, III-A, III-B, and IV-A and IV-B. These six scenarios are summarized in Table 5.

4 Simulation Results

4.1 Estimated "Domain of Attraction"

Based on the six scenarios summarized in Table 5, we run the Monte Carol simulation to estimate the ratios of the domain of attraction, to be compared with the those obtained in Yu, Chen and Li (2011). The way to do so is to *uniformly* sample a large number of initial distributions of strategies, $\mathbf{x_i(0)} = \{x_i(0)\}_{i=1}^{3\ or\ 4}$, in the simplex as illustrated shown in Figure 2, where $x_i(0)$ is the initial fraction of agents who follow strategies s_i ($i = 1, 2, 3, 4$). Clearly, $\sum_{i=1}^{3\ or\ 4}(t) = 1, \forall t$. In Figure 2, there is a total of 1,400 points, $\mathbf{x}_{i,n}(0)$ ($n = 1, ..., 1400$), being sampled. Furthermore, denote the number of players with good reputation among the three (four) strategies by g_i ($i = 1, 2, 3, (4)$). We assume that initially there is an equal chance of being a good agent or a bad agent for each strategy group, i.e. $g_i(0) = \frac{1}{2}100 \times x_i(0)$ for each i; hence, $g(0) = \sum_{i=1}^{3\ or\ 4} g_i(0) = 50$. Then for each single initial distribution $\mathbf{x}_{i,n}(0)$ we apply the agent-based model as described in Section 2 to generate the evolution of this distribution.

By tracing the path of each initial distribution $\mathbf{x_i(0)}$ up to its ending (convergence) ($\mathbf{x_i(t)}$, t large enough), we can then group these sample points into different domains of

Figure 2: A Uniformly Distributed Sampling of the Initial Fractions of Strategy Users (Left) and their Evolution (Right)

attraction, depending on their resting point, as also shown in Figure 2, right panel.[4]

As a further illustration, two typical runs of the design using coarser information (4) are shown in Figure 3, whereas another two typical runs of the design using finer information (5) are shown in Figure 4. Even though these are just two examples from each fitness function, it is interesting to notice that some remarkable differences between them already appearing. For example, for the two runs with the coarser information, regardless of the initial distribution, the whole population of agents eventually converge to a homogeneous society that all agents follow the strategy '*DD*' ((Figure 3, left panels). In other words, these two initial points are considered to be in the domain of the attraction to DD. The agents with good or bad reputation are half and half ($g(t) \approx 50$, t large enough) accordingly, as shown in Figure 3, right panel. However, if we look at the two cases under finer information, we find that one of them actually converge to the homogenous population of CD (Figure 4, lower left panel); hence this initial point is consider as a point from the domain of attraction to CD. This point ends up with all agents having good reputation ($g(t) \approx 100$, t large enough), as shown in Figure 4, lower right panel.

4.2 Pro-Social Behavior

The main argument of Yu, Chen and Li (2011) is the contribution of the strongly augmented social norm to the emergence of pro-social behavior, which largely speaking refers to a degenerated distribution on 'CC', 'CD' and 'CP', although in their analysis, 'CC' as an equilibrium has never happened, and it leaves us only 'CD' and 'CP' to look at. With this background, when making a comparison between the mean-field model and the agent-based model, we have to make a distinction between the *quantitative difference* and the *qualitative difference*. The former refers to the domain of attraction to each equilibrium point, whereas the latter refers to the emergence likelihood of the pro-social behavior, or, technically put, the sum of the domain of attraction to 'CC', 'CD' or 'CP'.

[4]Rigorously speaking, any single point in the simplex may not always end with the same limit point, since the agent interactions are very stochastic. However, we hope that this individual indeterminism can be averaged off when we have a large sample of different points, each independently having its own indeterminism.

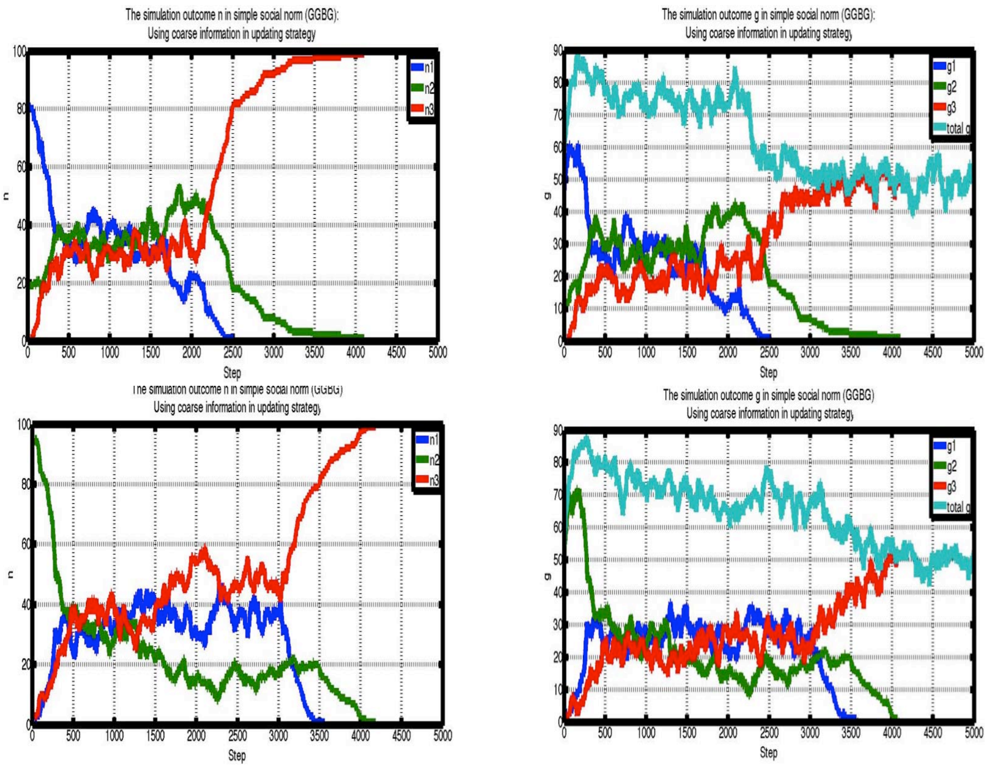

Figure 3: Evolution of Population Distribution under Simple Norm (“*GGBG*”): By Strategy (Left) and By Reputation (Right), Coarser Information

On this ground, we shall find that, despite their significant quantitative difference, there is no observed significant qualitative difference between the mean filed model and the agent-based model.[5] In fact, not only the quantitative differences exist between the mean-field model and the agent-based model, they can be observed in different versions of the agent-based model, across the design series I, II, and III, and A and B. Let us address each of the aforementioned points in the following.

4.2.1 Quantitative Differences

The estimated domain of attraction is summarized in Table 6 and 7, the former focusing on the design series I (high adaptation frequency), whereas the latter focusing on the design series II and III (medium and low adaptation frequencies).

The result shows that the agent-based simulation differs from the replicator dynamics in certain scenarios. First, we ask whether the simple social norm (the norm without punishment) will necessarily lead to the degenerated distribution on ‘DD’, having ‘DD’ as the only result. The answer is already no for the replicator dynamics. Even though in Yu, Chen and Li (2011) the strategy ‘DD’ is the most likely limiting point, it is not the only one, and ‘CD’ becomes another possibility. However, the answer from the agent-

[5] Yu, Chen and Li (2011) also made the analysis on the convergence speed, this part is hard to do on the same ground here since adaptation frequency itself is a parameter to manipulate in the agent-based model.

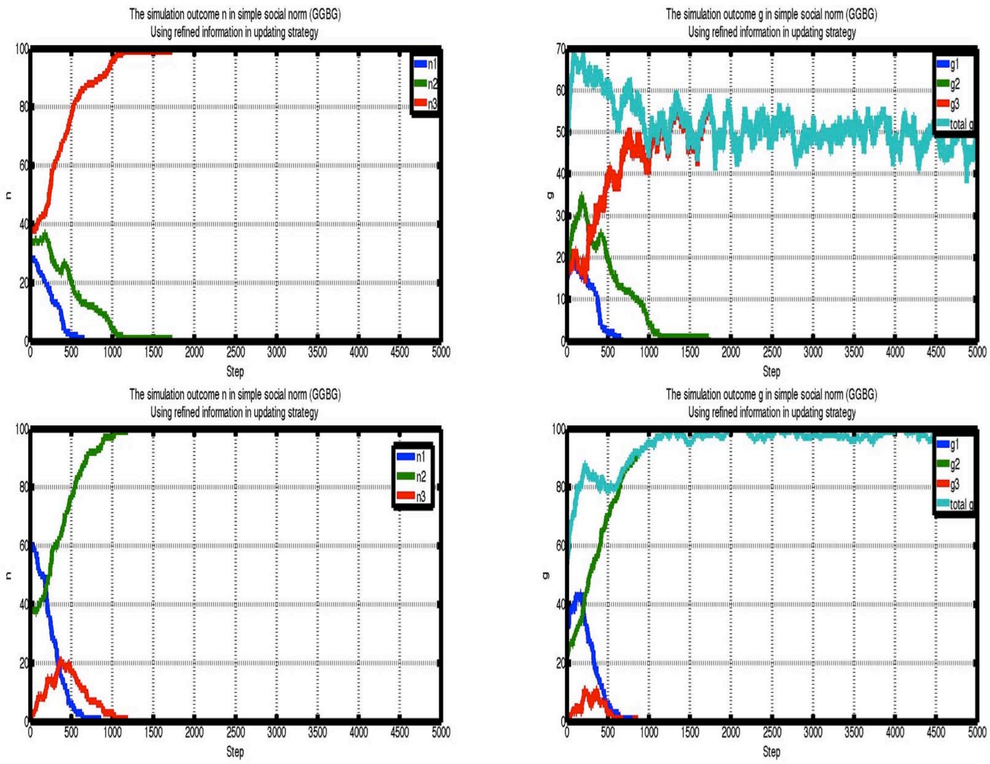

Figure 4: Evolution of Population Distribution under Simple Norm ("$GGBG$"): By Strategy (Left) and By Reputation (Right), Finer Information

based model varies, depending on the applied version. From Tables 6 and 7, we can see that 'DD' indeed becomes the only result under the scenario II-A and III-A, both having 100% domain of attraction to it. Even though in II-B and III-B, 'CD' also becomes possible, 'DD' remains to have more than 95% of the simplex as its attraction domain. In other words, the simple social norm can make the pro-social behavior harder to appear than the replicator dynamics has demonstrated when adapting frequency is not too long. Nevertheless, when coming to IV-A and IV-B, the domain of attraction to 'DD' decrease to a ratio very close to replicator dynamics. Hence, in this case, the agent-based model may 'converge' to the replicator dynamics when the adaption frequency is low enough. It is also worthy noting that 'CC', which never occurs under the scenario I, also now appears in II-B, IV-A and IV-B.

We then move to the second question: what happens when punishment is allowed, but not as an effective part of the norm? In this case, the replicator dynamics show that pro-social behavior will be the most likely result, although 'DD' still has 40% of the simplex as its domain. On this question, the agent-based models again have quite different answers. The ones whose results are closest to the replicator dynamics are III-B and IV-B, which have almost the same ratio for 'CD', i.e., 60%. On the other hand, II-B has the opposite result, which still keeps 'DD' as the dominant outcome with a ratio high up to 80%. As to the 'A' scenarios (II-A, III-A and IV-A), they all have 'CD' as the only possible equilibrium (100% for 'CD'). Very clearly, information granulation plays a more decisive role than the

Table 6: Distribution of Equilibrium: High Adaptation Frequency

	Simple Norm			Weakly Augmented Norm			Strongly Augmented Norm		
S	I	II-A	II-B	I	II-A	II-B	I	II-A	II-B
CC	0%	0%	0.25%	0%	0%	1.53%	0%	0%	5.60%
CD	15%	0%	0.25%	60%	100%	11.90%	0%	0%	7.80%
DD	85%	100%	99.5%	40%	0%	79.2%	19%	0%	37.7%
CP	NA	NA	NA	0%	0%	7.30%	81%	100%	48.9%

The distribution of equilibrium under meso-level dynamics (the replicator dynamics) is labelled by "I", and the one under micro-level dynamics is labeled by "II-A" if agents follow *coarser* social learning and by "II-B" if they follow *finer* information. The number appearing in the cell shows that the occurrence frequency of the convergence characterized by a homogeneous population using the 'CC', 'CD','DD', or 'CP' strategy. Under the scenario when the norm is strongly augmented and agents follow social learning, instead of converging to homogeneous population, we may have cases converging to a strange attractor, walking between 'CD' and 'DD'; in this case, the frequencies given are not exact, but are estimated based on neighbor to which the attractor is closer, either 'CD' or 'DD'.

adaptation frequency in accounting for the difference between the replicator dynamics and the agent-based simulation. As in the case of simple social norm, equilibria which do not occur in the replicator dynamics can happen in the agent-based models, such as 'CC' in the 'B' series, and 'CP' in II-B and III-B.

The social learning with coarser information (the 'A' sequence) always leads to a degenerate distribution, degenerating to 'DD', 'CD', and 'CP'. There is no exception; this is very different from either the replicator dynamics or the social learning with finer information.

Finally, we examine the effect when punishment is an effective part of the social norm. Under this strongly augmented norm, Yu, Chen and Li (2011) shows that 'CP' becomes the dominant equilibrium (81%), and 'DD' has shrunk further down to only 19%. Based on this result, Yu, Chen and Li (2011) argues the significance of the norms which value the costly punishment. This result in general is again confirmed by the agent-based modeling, except differing at a quantitative level. Among the six scenarios, II-B seems to be the one most different from the benchmark. As in the case of the weakly social norm, 'DD' is still quite active in this scenario, while its domain of attraction declines from the original 80% to only 40%. In this sense, the adoption of the strong augmented norm indeed has a great effect on the pro-social behavior. The other two 'B' scenarios (III-B and IV-B) both have slightly lower attraction domain of 'CP'; nonetheless since 'CC' also become as a possible attractor, the possibility of having pro-social behavior is even larger than that in the benchmark. As to the three 'A' scenarios, as in two previous norms, the result degenerates to the attractor which is the most likely result under the replicator dynamics and have a 100% attraction domain to 'CP'.

Table 7: Distribution of Equilibrium: Medium and Low Adaptation Frequency

Simple Norm					
S	I	III-A	III-B	IV-A	IV-B
CC	0%	0%	0.00%	1.30%	3.09%
CD	15%	0%	0.05%	9.79%	10.28%
DD	85%	100%	94.47%	88.91%	86.63%
CP	NA	NA	NA	NA	NA
Weakly Augmented Norm					
S	I	III-A	III-B	IV-A	IV-B
CC	0%	0%	3.3%	0%	7.05%
CD	60%	100%	61.73%	100%	60.47%
DD	40%	0%	34.81%	0%	32.44%
CP	0%	0%	1.5%	0%	0%
Strongly Augmented Norm					
S	I	III-A	III-B	IV-A	IV-B
CC	0%	0%	19.80%	0%	26.74%
CD	0%	0%	0.00%	0%	0.00%
DD	19%	0%	9.60%	0%	8.30%
CP	81%	100%	70.47%	100%	64.71%

The distribution of equilibrium under meso-level dynamics (the replicator dynamics) is labelled by "I", and the one under micro-level dynamics is labeled by "II" if agents follow *coarser* social learning and by "III" if they follow *finer* information. The number appearing in the cell shows that the occurrence frequency of the convergence characterized by a homogeneous population using the 'CC', 'CD','DD', or 'CP' strategy. Under the scenario when the norm is strongly augmented and agents follow social learning, instead of converging to homogeneous population, we may have cases converging to a strange attractor, walking between 'CD' and 'DD'; in this case, the frequencies given are not exact, but are estimated based on neighbor to which the attractor is closer, either 'CD' or 'DD'.

4.2.2 Qualitative Differences

5 Concluding Remarks

Agent-based models allow us to take into account of many fine details that the replicator dynamics may have difficult to capturing. Despite this limitation, we find that our agent-based model, qualitatively speaking, has generally led to same result as predicted by the replicator dynamic model. Specifically, its prediction of the emergence of the pro-social behavior is confirmed by several versions of the agent-based model. Discredit those who do not take measure to actively distinguish good-reputation agents from bad-reputation agents can largely enhance the appearance of cooperative behavior.

References

Aoki M, Yoshikawa H (2012) Non-self-averaging in macroeconomic models: A criticism of modern micro-founded macroeconomics. Journal of Economic Interactions and Coordination 7:1-12.

Burger M, Haskovec J, Wolfram M.-T (2013) Individual based and mean-field modelling of direct aggregation.

Fehr E, Gächter S (2002) Altruistic punishment in humans. Nature 415(6868):137-140.

Fisher F (1983) Disequilibrium Foundations of Equilibrium Economics. Cambridge University Press.

Gintis H (2007) The dynamics of general equilibrium. Economic Journal 117(523):1280-1309.

Hommes C (2006) Heterogeneous agent models in economics and finance. In: Tesfatsion L. Kenneth J (eds.) Handbook of Computational Economics, 2-23:1109-1186, Elsevier.

Ohtsuki H, Iwasa Y (2007) Global analyses of evolutionary dynamics and exhaustive search for social norms that maintain cooperation by reputation. Journal of Theoretical Biology 244(3):518-531.

Ohtsuki H, Iwasa Y, Nowak M (2009) Indirect reciprocity provides only a narrow margin of efficiency for costly punishment. Nature 457(7225):79-82.

Van Dyke Parunak H (2012) Between agents and mean fields.

Vinkovic D, Kirman (2006) A physical analogue of the Schelling model.

Yu T, Chen S.-H, Li H (2011) Social norm, costly punishment and the evolution to cooperation. MPRA Paper 28741, University Library of Munich, Germany.

The Formation of Risk-Sharing Networks

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Abstract

Previous studies find that people commonly construct risk-sharing network with their close neighbors, relatives, and friends (Udry 1994; Fafchamps and Lund 2003; Angelucci et al. 2012), but almost full global insurance can be achieved although the sizes of risk-sharing network are relatively small (Townsend 1994). In our study, we set up models to explain why in reality the size of risk-sharing network is small, and why people like to build up risk-sharing networks with those who have construct close relationship such as close neighbors, relatives, and friends. We attribute the small size of networks to the heterogeneous income distribution of individuals in society, and to the asymmetric information environment about people's incomes. Moreover, People like to set up risk-sharing network with good friends, close neighbors, and relatives due to the asymmetric information environment about people's incomes. In addition, we argue that infinite size of network is not necessary because when the size of network is large enough, the risk can be reduced to a very low level. In addition, we provide an explanation for the effectiveness of small size network observed by previous literatures.

Keywords: Social network; Risk-sharing; Agent-based Modeling;

JEL: D85, G22, O15, O17, Z13.

Introduction

In developing countries, due to the absence of formal insurance, some households especially those living in the countryside will construct risk-sharing networks to lower their consumption volatilities caused by crop failure, severe disease, large education spending, or other factors. The risk sharing behavior can be looked as reciprocity behavior and can only exist within stable social networks.

Kimball (1988) is among the first to show why people intend to form a cooperative to reduce risk by sharing income together under repeated game. Under autarky and homogenous income assumption, the theoretical expectation is that all members join a fully risk sharing group, but the empirical studies show that risk sharing usually are not taken within whole community (Fatchamps and Lund 2003; Murgai 2002; De Weerdt and Dercon 2006; Bold and Dercon 2009). To explain the boundary of groups, most theoretical studies try to adopt ex ante network formation cost or assign a cost when network increase. They either assume cost of formation like marriage or communication cost (Genicot and Ray 2003), or links exogenously exit like kinship or friendship (Ambrus 2014), or within communities, risk sharing groups/networks are not randomly formed (Fafchamps and Gubert 2007; Weerdt and Dercon 2006; Dekker 2004; Mazzocco and Saini 2008).

By studying the pattern of informal transfers and the effectiveness of risk-sharing network, development economists find that people commonly construct risk-sharing network with their close neighbors, relatives, and friends (Udry 1994; Fafchamps and Lund 2003; Angelucci et al. 2012), but almost full global insurance can be achieved although the sizes of risk-sharing network are relatively small (Townsend 1994).

To explain the seemingly contradictory findings, Bramoullé and Kranton (2007) propose that if individuals are committed to share income equally within pairs and interact repeatedly with their neighbors, they can end up sharing income equally within components of the network. This means that efficient networks can result in the equivalent of full-income pooling with a population, despite bilateral relations and commitment costs. In their model they assume that risk-sharing relationships are bilateral and establishing such a relation is costly. Ambrus et al. (2014) propose that close to perfect risk-sharing can be achieved for the type of more loosely connected social networks. Their model also indicates that households' consumption will commove more strongly with that of socially closer households.

However, why people try to set up risk-sharing network with their close neighbors, good friends or relatives, but not other people? Previous studies do not answer this question clearly, but only assume that links exogenously exist. Moreover, why there exists a network formation cost? How the cost is induced? The cost of formation like marriage or communication cost proposed by Genicot and Ray (2003) actually is the sunk cost, which can not guaranty the formation of a risk-sharing network unless all the members in the network can obtain benefits.

In our study, we try to set up theoretical models to explain these questions. Since most of previous theoretical studies assume an identical random income distribution, sharing income with other people will certainly bring them benefits by lowering the income risk but not affecting the income level. However, in reality, people's incomes can be distributed identically. In our study, we assume that the incomes will not be distributed identically, and different individuals have different expected levels of incomes. We find that it is hard for individuals with significantly different expected levels of incomes to build up a risk-sharing network. Therefore, the size of risk-sharing networks cannot be infinity in a society with limited population.

In our theoretical model, agents have random incomes with zero correlation between any two agents, and they can form networks by equally sharing their incomes. Moreover, agents are risk averse, the utility of agent will be positively correlated to the income expectation, and negatively correlated to the variance of income. Then, sharing their incomes with other agents may lower their income risks, which means they could decrease the probability of experiencing occasional very low income. However, sharing income with other agents with low incomes may lead to a lower income expectation. Under this situation, agents will make decision on whether they like to construct a risk-sharing network based on the trade-off between their reduced incomes and decreased volatilities of their incomes. Agents may also experience increased incomes and increased volatilities of incomes. Then they also need to make decision on whether to construct a new network based on the trade-off between their increased income and increased volatilities of incomes. Overall, agents will decide to construct a new network only when their utilities increase after they construct the network.

Our theoretical analysis indicates that the difference between the lowest and highest income of the agents in the networks will be smaller than a value that is decided by the number of agents in the network and variances of agents' incomes. Therefore, different levels and variances of incomes will lead to different types of risk-sharing networks. Agents tend to construct the network with the similar incomes, and are not like to form the network due to large difference between the incomes of agents. This result is consistent with reality, because it is very had to form a risk-sharing network by a high-income family and a low-income family. Otherwise, the high-income family will do too much favor to the low-income family, and in the long run, high-income family will break the connection between them. The network formed by two families with same income level actually performs reciprocal behavior. One family will do a favor to another for sometimes, and the other family will do a favor to the former family other time. On average, families obtain zero net income from the other one, but they get help when they need a favor.

Moreover, this study assumes that the income information is asymmetric, and this means that individuals cannot observe the mean and variance of other people’s incomes before they set up a risk-sharing network with others. We assume that for convenience, there are still only two types of agents, high-income and low-income agents, and they will share incomes randomly. High-income agents are facing the adverse selection risk. When the high-income agents share incomes with low-income agents, the utility of the high-income agents will decrease, and only when the high-income agents share incomes with high-income agents, the utility of the high-income agents will increase. Therefore, high-income agents decide to construct a new network only when the expected utility after the new network is constructed is higher than otherwise. Low-income agents will like to construct networks with any agents, because they will benefit all the time from the networks due to higher utilities than otherwise. Since when information is asymmetric individuals may decrease their utilities when they share their incomes with low income people, setting up a risk-sharing network with good friends, close neighbors, or relatives will be a better choice because people can receive more precise income information from those that have set up close relationship with them than from other people.

Based on the above assumptions, our theoretical analysis shows that the size of the networks built by high-income agents cannot be too large, and it is determined by the difference between the income levels of high- and low-income agents, the probability of high-income agents sharing incomes with low-income agents, and the variance of the incomes. The larger the difference between the incomes of high- and low-income agents, the smaller the maximum size of network is. The higher of the probability of low-income agents, the smaller of the maximum size of network is. In addition, the higher the variance of agents' income, the larger of the maximum size of network is.

We can extend our model to the situation under which there are more than two levels of agents' incomes. Except for the agents with lowest income level, other agents will also face this kind of adverse selection risk. Therefore, the size of networks for different levels of incomes may be different, and it will be also related to income deviation, distribution of different income level agents, and the variance of agents' incomes. This model can explain why in reality people commonly like to select relatives and friends to construct risk-sharing networks, and the size of networks will not be too large.

In addition, our theoretical model also indicates that the process of forming a network will affect the size of network. For example, if there is no cost of building up a network between agents, there are only two types of agents, high-income and low-income agents with same level of risks, and the difference of income levels between high- and low-income agents is large enough, all of the high-income agents will join one network and all low-income agents will join another network. However, if the difference of income levels between high- and low-income agents lies in a range, four independent agents, including two high-income and two low-income agents, will build up a network due to higher utility than otherwise. Nevertheless, a network composed by two high-income agents may not construct a new network with another network composed by two low-income agents. Therefore, the networks may be built in different ways, which may lead to the network composed with different types of agents and different sizes. However, the efficient network with highest utility will be unique, and the size may be smaller than the maximum size that a network can reach.

Risk-Sharing Models

In a society of *n* individuals, each individual *i* obtain an exogenous random income, $y_i \sim N(\overline{y_i}, \sigma_i^2)$, which is normally, and independently distributed with mean $\overline{y_i}$ and variance σ_i^2. Individuals are risk-averse and have to face shocks to their incomes. People have identical preferences and their utility function is $u = \overline{y} - \lambda\sigma^2$, which is increasing with the income levels and reducing with the shocks to their incomes. Since formal insurance markets are not available in this society, the only way for people to mitigate risk is to make insurance arrangement with others in this society. We assume people only share their risk after they form risk-sharing groups together. Once they share risk together, each individual in the shared group should have an identical random income $y \sim N(\frac{\sum_{i=1}^{n}\overline{y_i}}{n}, \frac{\sum_{i=1}^{n}\sigma_i^2}{n^2})$. Before risk sharing, the utility of a single individual *i* is $u_i = \overline{y_i} - \lambda\sigma_i^2$, and after sharing risk, the utility of the individual *i* becomes $u_i' = u' = \frac{\sum_{i=1}^{n}\overline{y_i}}{n} - \lambda\frac{\sum_{i=1}^{n}\sigma_i^2}{n^2}$. Therefore, the change in utility for each individual will be $\Delta u_i = u' - u_i = \frac{\sum_{i=1}^{n}\overline{y_i}}{n} - \lambda\frac{\sum_{i=1}^{n}\sigma_i^2}{n^2} - (\overline{y_i} - \lambda\sigma_i^2)$. Therefore, only when $\Delta u_i > 0$, the individual *i* will choose to join the risk sharing group.

For convenience, we assume that the expectation and the volatilities of income are same for all the people. Then we have $\overline{y_i} = \overline{y}$, and $\sigma_i^2 = \sigma^2$. Then we have the change in utility $\Delta u_i = \overline{y} - \lambda\frac{\sigma^2}{n} - (\overline{y} - \lambda\sigma^2) = \lambda(1-\frac{1}{n})\sigma^2$. Since for a risk-sharing group, the number of individuals in the group will at least be 2, the $\Delta u_i > 0$ will be satisfied naturally. This result means that for individuals with identical incomes, sharing income will definitely increase their utilities by lowering their risk but not changing their expected income level. Moreover, we can know that the larger the number of group members, the greater the change in utility is. Therefore, for the situation of identical income distribution, people try to set up a risk-sharing network with infinity size. However, in reality, when *n* is large enough, the risk of income can be lowered to a very small level, and then the probability that people experience very bad situation will be very low. Moreover, systematic risk such as crop failure caused by very bad weather will influence all the society and this kind of risk cannot be reduced by risk-sharing within the society. So, it is impossible for people to lower their risk to zero by setting up a network with infinite number of people. In reality, the large systematic risk will be rare. Therefore, without observing systematic risk, the effectiveness of relatively small network may be very near to full insurance.

Consider that an individual $n + 1$ will join the group with *n* members, only if the individual's utility after risk sharing will be greater than the utility before risk sharing. Then we have $\frac{\sum_{i=1}^{n+1}\overline{y_i}}{n+1} - \lambda\frac{\sum_{i=1}^{n+1}\sigma_i^2}{(n+1)^2} - (\overline{y_{n+1}} - \lambda\sigma_{n+1}^2) > 0$. This inequality can be derived into following inequality:

$$\overline{y_{n+1}} - \frac{\sum_{i=1}^{n}\overline{y_i}}{n} < \frac{\lambda}{n+1}[(n+2)\sigma_{n+1}^2 - \frac{\sum_{i=1}^{n}\sigma_i^2}{n}]. \quad (1)$$

This means when this inequality relation is satisfied the utility of individual *i* will increase, and the individual *i* will like to join the group. At the same time when the individual *i* choose whether joins the group, the group members also need to consider whether permit the individual *i* joining the group. Consider that a group with *n* members will include a person *n+1* into the group, only if

$$\frac{\sum_{i=1}^{n+1}\overline{y_i}}{n+1} - \lambda\frac{\sum_{i=1}^{n+1}\sigma_i^2}{(n+1)^2} - (\frac{\sum_{i=1}^{n}\overline{y_i}}{n} - \lambda\frac{\sum_{i=1}^{n}\sigma_i^2}{n^2}) > 0.$$

We then can obtain,

$$\overline{y_{n+1}} - \frac{\sum_{i=1}^{n}\overline{y_i}}{n} > \frac{\lambda}{n+1}(\sigma_{n+1}^2 - \sum_{i=1}^{n}\sigma_i^2 \frac{2n+1}{n^2}). \quad (2)$$

When this inequality is satisfied, the utility of group members will increase and the group will like to permit individual *i* to join the group. Therefore, only when both the individual's utility and group members' utilities increase after the individual join the group, the new risk-sharing group can be set up. This means only when both the inequality equation (a) and (b) are satisfied, the new group will be constructed.

So, combining $\overline{y_{n+1}} - \frac{\sum_{i=1}^{n}\overline{y_i}}{n} < \frac{\lambda}{n+1}[(n+2)\sigma_{n+1}^2 - \frac{\sum_{i=1}^{n}\sigma_i^2}{n}]$ and

$\frac{\sum_{i=1}^{n}\overline{y_i}}{n} - \overline{y_{n+1}} < \frac{\lambda}{n+1}(\sum_{i=1}^{n}\sigma_i^2 \frac{2n+1}{n^2} - \sigma_{n+1}^2)$, we have:

$$\frac{\lambda}{n+1}(\sigma_{n+1}^2 - \sum_{i=1}^{n}\sigma_i^2 \frac{2n+1}{n^2}) < \overline{y_{n+1}} - \frac{\sum_{i=1}^{n}\overline{y_i}}{n} < \frac{\lambda}{n+1}[(n+2)\sigma_{n+1}^2 - \frac{\sum_{i=1}^{n}\sigma_i^2}{n}] \quad (3)$$

The inequalities imply that $\frac{\lambda}{n+1}(\sigma_{n+1}^2 - \sum_{i=1}^{n}\sigma_i^2 \frac{2n+1}{n^2}) < \frac{\lambda}{n+1}[(n+2)\sigma_{n+1}^2 - \frac{\sum_{i=1}^{n}\sigma_i^2}{n}]$ should be satisfied. We derive it into following style, $\sum_{i=1}^{n}\sigma_i^2(-\frac{1}{n^2}) < \sigma_{n+1}^2$. Since left side is negative and right side is positive, this inequality will be always satisfied. This result indicates that only when the difference between the individual's expected income and group members' expected income is small enough, the new group, which is composed with the individual and group members, can be built up. Since the income difference between different people might be very large in one society, the risk-sharing group cannot be composed by all the people in that society. In reality, we can hardly find a risk-sharing group that will include all the people in the society.

For convenience, we assume the volatilities of income are same for all the people. Then we have $\sigma_i^2 = \sigma^2$, and above inequalities will be modified into

$$\frac{\lambda}{n+1}(-\frac{n+1}{n})\sigma^2 < \overline{y_{n+1}} - \frac{\sum_{i=1}^{n}\overline{y_i}}{n} < \frac{\lambda}{n+1}(n+1)\sigma^2 .$$

Here we assume that before one single individual joins a risk-sharing group, he/her has not yet joined any group. This situation can be happened when an individual begins to share risk with other people. However, when all the people have already joined at least one group, we need to consider one more common situation that before an individual plans to join the group with *n* members, he/she has been stayed in a group with *m* members. For this situation, the group with *n* members will permit the individual join their group if following inequality is satisfied:

$\frac{\sum_{i=1}^{n+1}\overline{y_i}}{n+1} - \lambda\frac{\sum_{i=1}^{n+1}\sigma_i^2}{(n+1)^2} - (\frac{\sum_{i=1}^{n}\overline{y_i}}{n} - \lambda\frac{\sum_{i=1}^{n}\sigma_i^2}{n^2}) > 0$. This inequality is same as in the situation that one single individual tries to join a group with *n* members. The individual will make decision on whether he/her joins the new group based on whether individual's utility after joining the new group will be greater than the utility staying in the old group. The following inequality will be satisfied:

$\frac{\sum_{i=1}^{n+1}\overline{y_i}}{n+1} - \lambda\frac{\sum_{i=1}^{n+1}\sigma_i^2}{(n+1)^2} - (\frac{\sum_{j=1}^{m}\overline{y_j}}{m} - \lambda\frac{\sum_{j=1}^{m}\sigma_j^2}{m^2}) > 0$. Then, only both inequalities are satisfied, the individual will leave the old group and join the new group.

For the convenience, we assume the volatilities of income are same for all the people. Then we have $\sigma_i^{\ 2} = \sigma^2$, and above inequality equations will be modified into

$\frac{\sum_{i=1}^{n+1}\overline{y_i}}{n+1} - \lambda\frac{\sigma^2}{n+1} - (\frac{\sum_{i=1}^{n}\overline{y_i}}{n} - \lambda\frac{\sigma^2}{n}) > 0$, and $\frac{\sum_{i=1}^{n+1}\overline{y_i}}{n+1} - \lambda\frac{\sigma^2}{n+1} - (\frac{\sum_{j=1}^{m}\overline{y_j}}{m} - \lambda\frac{\sigma^2}{m}) > 0$.

For a very special case, when the expected incomes are same for all the people in the society, the above inequality will be derived to $\frac{1}{n}-\frac{1}{n+1}>0$, and $\frac{1}{m}-\frac{1}{n+1}>0$. For all *n*, when $n \geq 1$, the inequality $\frac{1}{n}-\frac{1}{n+1}>0$ will be true. Therefore, we obtain $n+1>m$, for the second inequality. This means that when the size of new group after the individual join it is larger than the size of old group when the individual has stayed in, the individual will leave the old group and join the new group.

Moreover, we consider the situation when the information is asymmetric. This assumption is reasonable because we cannot observe other people's full information about their incomes in reality. Under this assumption, one individual does not know any information about the incomes of other individuals before they share his/her income with others. Once the individuals equally share incomes with other individuals, they can obtain the full or partial income information about other individuals. Therefore, before obtaining the information about other people's incomes, people will randomly share their income with other people. After obtaining the income information about others, people will make decision whether to share incomes with others or not based on their utility functions.

For the convenience, we assume there are two kinds of individuals with either high-level incomes or low-level incomes. For high-level income individuals, their utilities are defined by $u_H = \overline{y_H} - \lambda\sigma^2$. The low-level income individuals' utilities are defined by $u_L = \overline{y_L} - \lambda\sigma^2$. Here, the variances of income for all the individuals are equal. Moreover, we assume that in the society, the probability of meeting a high-income individual is *p1* and the probability of meeting a low-income individual is *p2*. Once the low-income individual share income with either high-income or low-income individual, the utility of this low-income individual will increase, but once the high-income individual share income with low-income individual, the utility of this high-income individual might reduce. Moreover, the high-income individuals will benefit from sharing their income with high-income individuals. Therefore, for high-income individuals, they will concern the probability that their utility will reduce once they share their income with low-income individual. Under the situation when a group with *n* high-income individuals meet an unknown individual, which might be a high-income individual with the probability of *p1*, or a low-income individual with the probability of *p2*, the high-income group will consider whether they will share their income with the unknown individual, based on the expected utility change.

The utility of the group with *n* high-income individuals will be $U_G = \overline{y_H} - \lambda \frac{\sigma^2}{n}$. Once they share their income with group with one high-income individual, then the utility will become $U_G' = \overline{y_H} - \lambda \frac{\sigma^2}{n+1}$. Once they share their income with a low-income individual, then the utility will become $U_G' = \frac{n\overline{y_H} + \overline{y_L}}{n+1} - \lambda \frac{\sigma^2}{n+1}$. Then the expected utility will be $E(U_G') = p1 \cdot (\overline{y_H} - \lambda \frac{\sigma^2}{n+1}) + p2 \cdot (\frac{n\overline{y_H} + \overline{y_L}}{n+1} - \lambda \frac{\sigma^2}{n+1})$.

Therefore, the expected change in utility will be

$E(U_G') - U_G = p1 \cdot (\overline{y_H} - \lambda \frac{\sigma^2}{n+1}) + p2 \cdot (\frac{n\overline{y_H} + \overline{y_L}}{n+1} - \lambda \frac{\sigma^2}{n+1}) - (\overline{y_H} - \lambda \frac{\sigma^2}{n})$. Only when the expected change in utility is greater than zero, high-income group will try to add a new member into their group, or they will stop to enlarge their size of group. Then we obtain the inequality:

$$p1\cdot(\overline{y_H}-\lambda\frac{\sigma^2}{n+1})+p2\cdot(\frac{n\overline{y_H}+\overline{y_L}}{n+1}-\lambda\frac{\sigma^2}{n+1})-(\overline{y_H}-\lambda\frac{\sigma^2}{n})>0\,.$$

Finally when the following inequality is satisfied, the high-income group will enlarge the group's size : $\lambda\frac{\sigma^2}{n}>p2(\overline{y_H}-\overline{y_L})$. Since $\overline{y_H}-\overline{y_L}>0$, when *n* is large enough, the inequality cannot be satisfied. This means when the size of high-income group is large enough, the group will not share income with other individuals. Therefore, the group will not be too large, because when the group is large enough the increase in the utility induced by reduced risk can not compensate the loss induced by lowered income due to sharing with low-income individual.

For all above situations, we consider that each time only one individual tries to join a risk-sharing network. However, in reality it will be true that more than one individual try to join a risk-sharing group simultaneously or one risk-sharing group will combine with another risk-sharing group. Here, we want to know whether different process of constructing risk-sharing network will induce different risk-sharing networks in a society.

Assuming there are *n* high-income individuals, and *n* low-income individuals, the utility of individual high-income individual are defined by $U_H=\overline{y_H}-\lambda\sigma^2$, and the utility of individual low-income individual are defined by $U_L=\overline{y_L}-\lambda\sigma^2$.
The *2n* individuals can construct a network if the utility of the network contains *2n* individuals is greater than individual utility of each individuals. Then, the network's utility will be $U'=\frac{\overline{y_H}+\overline{y_L}}{2}-\lambda\frac{\sigma^2}{2n}$. The increase in utility for high-income

individuals will be $\Delta U = U' - U_H = \frac{\overline{y_H} + \overline{y_L}}{2} - \lambda \frac{\sigma^2}{2n} - (\overline{y_H} - \lambda\sigma^2)$. Only when $\Delta U > 0$, These *2n* individuals can form the network. Therefore, we have $\frac{\overline{y_H} + \overline{y_L}}{2} - \lambda \frac{\sigma^2}{2n} - (\overline{y_H} - \lambda\sigma^2) > 0$. We finally obtain when $\overline{y_H} - \overline{y_L} < \lambda\sigma^2 \frac{2n-1}{n}$ is satisfied then these individuals will form a network to share their income.

For another process of forming network, we suppose that high-income individuals form a network, then the utility will be $U'_H = \overline{y_H} - \lambda \frac{\sigma^2}{n}$, and low-income individuals form a network with utility function: $U'_L = \overline{y_L} - \lambda \frac{\sigma^2}{n}$. Then we can find that if the two networks can build a larger network, the utility of this larger network will be $U' = \frac{\overline{y_H} + \overline{y_L}}{2} - \lambda \frac{\sigma^2}{2n}$, which is same as the utility of network formed by *2n* individuals directly. Therefore, only when $\Delta U = U' - U'_H = \frac{\overline{y_H} + \overline{y_L}}{2} - \lambda \frac{\sigma^2}{2n} - (\overline{y_H} - \lambda \frac{\sigma^2}{n}) > 0$. To satisfy this inequality, we get $\overline{y_H} - \overline{y_L} < \lambda\sigma^2 \frac{1}{n}$. When *n* high-income individuals and *n* low-income individuals try to construct a network, the difference between the income levels of high- and low-income individuals can be very large, but when a network composed with *n* high-income individuals try to build up a new network with a network composed with *n* low-income individuals, the difference between the income levels of high- and low-income individuals will be much smaller. Therefore, when $\lambda\sigma^2 \frac{1}{n} < \overline{y_H} - \overline{y_L} < \lambda\sigma^2 \frac{2n-1}{n}$, then the *2n* individuals can form a network, but two networks respectively composed with *n* high-income individuals and *n* low-income individuals will not form a larger network. So, the process of forming network will affect the network size and components in it.

Conclusions

Our theoretical model provides two possible reasons for the small size of networks in reality. One is due to heterogeneous income distribution of individuals in society. Another is due to information about income is asymmetric. People like to set up risk-sharing network with good friends, close neighbors, and relatives to lower the costs induced by sharing income with low-income individuals when information is asymmetric. Of course, they will definitely set up network with high-income individuals among those people with close relations.

Moreover, we argue that infinite size of network is not necessary because when the size of network is large enough, the risk can be reduced to a very low level. In addition, since systematic risk cannot be diversified, it is useless to set up an infinite size network. Without observing systematic risk, the effectiveness of relatively small network may be very near to full insurance. Therefore, we also provide an explanation for the effectiveness of small size network observed by previous literatures.

References

Ambrus, Attila, Markus Mobius, and Adam Szeidl. 2014. "Consumption Risk-Sharing in Social Networks." *American Economic Review*, 104(1): 149-82.

Angelucci, M., De Giorgi, G., and Rasul, I. 2012. Resource Pooling Within Family Networks: Insurance and Investment.

Attanasio, O., Barr, A., Cardenas, J. C., Genicot, G., & Meghir, C. (2012). "Risk Pooling, Risk Preferences, and Social Networks". *American Economic Journal: Applied Economics*, *4*(2), 134-167.

Bloch F, Genicot G, Ray D. 2008. Informal insurance in social networks. *Journal of Economic Theory* 143(1): 36-58.

Bold, T., and Dercon, S. 2009. *Contract design in insurance groups*. Department of Economics, University of Oxford.

Bramoullé Y, Kranton R. Risk-sharing networks. *Journal of Economic Behavior & Organization*, 2007, 64(3): 275-294.

Bramoullie Y, Kranton R. Risk sharing across communities. *The American Economic Review*, 2007, 97(2): 70-74.

Bramoullé Y, Fortin B. The econometrics of social networks. Cahier de recherche/Working Paper, 2009, 9: 13.

Cox D, Jimenez E. Risk sharing and private transfers: What about urban households?. *Economic Development and Cultural Change*, 1998, 46(3): 621-637.

Coate, Stephen and Ravallion, Martin. (1993): "Reciprocity without Commitment: Characterization and Performance of Informal Insurance Arrangements," Journal of Development Economics, 40, 1-24.

De Weerdt, J., and Dercon, S. 2006. Risk-sharing networks and insurance against illness. *Journal of Development Economics*, *81*(2), 337-356.

Dekker, M. 2004. Risk sharing in rural Zimbabwe: an empirical analysis of endogenous network formation. In *Unpublished, paper presented at the CSAE Conference on growth, poverty reduction and human development*.

Fafchamps M, Lund S. 2003. Risk-sharing networks in rural Philippines. *Journal of development Economics* 71(2): 261-287.

Fafchamps, M., Gubert, F. 2007. The formation of risk sharing networks. *Journal of Development Economics* 83(2): 326-350.

Fafchamps, M., and Gubert, F. 2007. Risk sharing and network formation. *The American economic review*, *97*(2), 75-79.

Genicot, G., and Ray, D. 2003. Group formation in risk-sharing arrangements. *The Review of Economic Studies* 70(1): 87-113.

Jackson M O, Watts A. The evolution of social and economic networks. *Journal of Economic Theory*, 2002, 106(2): 265-295.

Kimball, Miles (1988): "Farmer Cooperatives as Behavior Towards Risk," American Economic Review, 78, 224-232.

Ligon, E., Thomas, J., and Worrall, T. 2002: "Mutual Insurance and Limited Commitment: Theory and Evidence in Village Economies," Review of Economic Studies, 69, 115-139.

Mazzocco, M. and Saini, S. 2007. Testing Efficient Risk Sharing with Heterogeneous Risk Preferences: Semi-Parametric Tests with and Application to Village Economies, mimeo.

Murgai, R., Winters, P., Sadoulet, E., and Janvry, A. D. 2002. Localized and incomplete mutual insurance. *Journal of Development Economics*, *67*(2), 245-274.

Udry C, Conley T. Social networks in Ghana. Yale University Economic Growth Center Discussion Paper, 2004 (888).

Townsend, R. M. 1994. Risk and insurance in village India. *Econometrica: Journal of the Econometric Society*, 539-591.

科技部補助計畫衍生研發成果推廣資料表

日期:2014/06/03

<table>
<tr><td rowspan="3">科技部補助計畫</td><td>計畫名稱: 以代理人基模擬及真人實驗探究良善社會複雜性之五元素</td></tr>
<tr><td>計畫主持人: 陳樹衡</td></tr>
<tr><td>計畫編號: 101-2410-H-004-010-MY2　　學門領域: 數理與數量方法</td></tr>
<tr><td colspan="2">無研發成果推廣資料</td></tr>
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101 年度專題研究計畫研究成果彙整表

計畫主持人：陳樹衡	計畫編號：101-2410-H-004-010-MY2
計畫名稱：以代理人基模擬及真人實驗探究良善社會複雜性之五元素	

成果項目			量化：實際已達成數（被接受或已發表）	量化：預期總達成數(含實際已達成數)	量化：本計畫實際貢獻百分比	單位	備註（質化說明：如數個計畫共同成果、成果列為該期刊之封面故事...等）
國內	論文著作	期刊論文	0	0	100%	篇	
		研究報告/技術報告	0	0	100%		
		研討會論文	0	0	100%		
		專書	0	0	100%		
	專利	申請中件數	0	0	100%	件	
		已獲得件數	0	0	100%		
	技術移轉	件數	0	0	100%	件	
		權利金	0	0	100%	千元	
	參與計畫人力（本國籍）	碩士生	0	0	100%	人次	
		博士生	0	0	100%		
		博士後研究員	1	100	100%		
		專任助理	1	100	100%		
國外	論文著作	期刊論文	17	17	100%	篇	
		研究報告/技術報告	0	0	100%		
		研討會論文	23	23	100%		
		專書	8	8	100%	章/本	章
	專利	申請中件數	0	0	100%	件	
		已獲得件數	0	0	100%		
	技術移轉	件數	0	0	100%	件	
		權利金	0	0	100%	千元	
	參與計畫人力（外國籍）	碩士生	0	0	100%	人次	
		博士生	0	0	100%		
		博士後研究員	0	0	100%		
		專任助理	0	0	100%		

其他成果 (無法以量化表達之成果如辦理學術活動、獲得獎項、重要國際合作、研究成果國際影響力及其他協助產業技術發展之具體效益事項等，請以文字敘述填列。)	由於本人十餘年來積極參與由 the Society for Computational Economics (SCE)所主辦的年會：Conference of Computing in Economics and Finance (CEF)，2013 年中終於爭取到該會於 2015 來台主辦權，此期計畫期間，並不斷從事宣傳活動，冀望維持該會歷年的平均參會人數（近 300 人）。同時，在 2013 年底的 EAEPE2013 會議之中，結識了 Ben Vermeulen (University of Hohenheim)，我們同時對模組化經濟有著相同的概念，因此於 2014 年 6 月間，共同提出了 DAAD 雙邊計畫，為彼此的國際合作打開了敘幕。其他學術活動，請見期末報告。

	成果項目	量化	名稱或內容性質簡述
科教處計畫加填項目	測驗工具(含質性與量性)	0	
	課程/模組	0	
	電腦及網路系統或工具	0	
	教材	0	
	舉辦之活動/競賽	0	
	研討會/工作坊	0	
	電子報、網站	0	
	計畫成果推廣之參與（閱聽）人數	0	

科技部補助專題研究計畫成果報告自評表

請就研究內容與原計畫相符程度、達成預期目標情況、研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）、是否適合在學術期刊發表或申請專利、主要發現或其他有關價值等，作一綜合評估。

1. 請就研究內容與原計畫相符程度、達成預期目標情況作一綜合評估

   ■達成目標

   □未達成目標（請說明，以 100 字為限）

   　　□實驗失敗

   　　□因故實驗中斷

   　　□其他原因

   說明：

2. 研究成果在學術期刊發表或申請專利等情形：

   論文：■已發表 □未發表之文稿 □撰寫中 □無

   專利：□已獲得 □申請中 ■無

   技轉：□已技轉 □洽談中 ■無

   其他：（以 100 字為限）

3. 請依學術成就、技術創新、社會影響等方面，評估研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）（以 500 字為限）